Luck Feelings, Luck Beliefs, and Decision Making

Harold W. Willaby

Psychology

University of Sydney

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1. Reviewer: Anonymous

2. Reviewer: Michael J. A. Wohl

3. Reviewer: Peter R. Darke

Signature from head of PhD committee:

Abstract

Luck feelings have long been thought to influence decision-making involving risk. Previous research has established the importance of prior outcomes, luck beliefs, and counterfactual thinking in the generation of luck feelings, but there has been no comprehensive demonstration of this system of variables that impinge on luck feelings. Moreover, the actual relationship of luck feelings and risky choice has not been directly tested. Addressing these gaps, results from five studies are presented in this thesis. Empirical work begins with an extensive validation exercise of an existing 22-item luck beliefs scale. Those 22 items are refined to a 16-item scale, comprising four luck belief dimensions that inter-relate in a compelling structural arrangement. Insights from this exercise, and a subset of the items are used throughout the remainder of the thesis. Results from two studies contradicted the counterfactual closeness hypothesis, the most prominent theory in the psychology of luck, which holds that counterfactual thinking is essential for generating lucky feelings. However, one study found that affect and luck feelings are not unitary, as evidenced by a weak form of double dissociation of affect and lucky feelings from overestimation and overplacement. Another study found lucky and unlucky feelings to be distinct. The effects of lucky feelings and unlucky feelings on risky choice differ by the nature of a prior outcome. For negative outcomes, unlucky feelings are likely to influence risky choices. For positive outcomes, lucky feelings are likely to influence risky choices. The type of risky choice most affected by lucky feelings—for positive experiences—is ambiguity tolerance in the probability distributions of prospective outcomes. The Activation Theory of Luck Feelings (ActLF) is proposed, which reconciles previous findings to those reported herein.

To my family.

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It is with a poignant sense of the passage of time that I reflect on the many supportive colleagues, friends, and of course family members that have urged me along toward this present moment. The journey began, it seems, so long ago that the memories are misty.

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Chapter 1

Introduction

In a famous scene from the 1971 movie, *Dirty Harry*, Harry Callahan (played by Clint Eastwood) faces down a bank robber. The bank robber contemplates reaching for a loaded shotgun. Harry challenges the bank robber:

> I know what you're thinking. 'Did he fire six shots or only five?' Well, to tell you the truth, in all this excitement I kind of lost track myself. But being as this is a .44 Magnum, the most powerful handgun in the world, and would blow your head clean off, you've got to ask yourself one question:
>
> *'Do I feel lucky?'*
>
> Well, do ya, punk?

The bank robber surrenders, presumably not feeling lucky enough to risk that Dirty Harry had only fired five shots from his six-chamber revolver.

This scene dramatically plays on the commonly held assumption that feeling lucky leads to greater risk taking. But, apart from Hollywood scripts, does "feeling lucky" influence decisions? In service of this question, the work before you refines a measure of luck beliefs, proposes and tests experimental manipulations of lucky feelings, and using a modelling approach, concludes that risky choice is affected by lucky feelings. However, the way in which lucky feelings operate is contingent on the context, the prior outcome, and beliefs in luck.

1.1 Chapter Overview

In this chapter, I review the concepts that relate to lucky feelings. There are five major sections. Section 1.2 examines the concept of luck through a historical lens, culminating with modern-day uses of the term. Of the many uses of the term 'luck', many are of no interest in the present work. However an appreciation of the many ways that humans have viewed luck, as well as the possible origins of the concept—grappling with the uncertainty inherent to the human condition—is useful to set the context for the phenomenon of lucky feelings. Section 1.3 addresses the question, "What is luck?" A formal definition of luck is proposed, upon which the remainder of the work can be built. Section 1.4 introduces the idea of luck attribution; the assignment of luck as relating to some outcome or set of outcomes. Section 1.5 introduces luck belief as a multi-dimensional construct. Belief in luck is proposed to moderate environmental stimuli to take on a luck-signal quality. Luck beliefs are therefore an important consideration in the genesis of lucky feelings and their influence on risky choice. Finally, in Section 1.6 is an extended treatment of lucky feelings, attempting to formally define the construct using a semantic and phenomenological approach. Some factors that could give rise to lucky feeling are proposed.

1.2 'Luck': Origins and Modern Day Use

The idea of luck has been part of human thought for millennia (Cohen, 1960). Consider Sun Tzu's advice dating to as early as 480 BCE: "Be prepared, and you will be lucky." Only a few hundred years later, Polybius, the Roman philosopher-historian struggled with attributions of Rome's success to strategic nous or Tyche[1] (Walbank, 1979, pp. 27-30).

The etymology of 'luck' is quite intricate, which is perhaps not surprising given the almost ubiquitous existence of the concept of luck across cultures and time. The word 'luck' only entered the English language in the late 15th century, from Middle High German, *gelücke*, meaning fate, fortune, prosperity, success, or favourable circumstances. In turn, *gelücke* was originally from the Old Norse word, *lukka*. A second word for

[1] Tyche was the Roman goddess who embodied chance and the more modern concept communicated by the term *luck*, as well as concepts of providence and fate. According to Walbank, Tyche was advanced by Polybius as a causal force when rational explanations were exhausted.

'luck' in Norse, *happ*, gave rise to the word 'happy' in modern English in the late 14th century. 'Happ' is also the origin of the word happen, meaning to occur by chance. An example of luck being intertwined with happiness, apparently independently from the Old Norse is alluded to in Taleb (2010, pp. 320-321):

> At some point in history the same Latin word, *felix* (from *felicitas*) was used to designate both someone lucky and someone happy. (The conflation of happiness and luck was explainable in an antique context: the goddess Felicitas represented both.) ...An ancient would have seen the distinction between the two concepts as a waste, since all lucky people seem happy (not thinking that one could be happy without being lucky).

The conflation of luck with other concepts such as happiness, chance and prosperity is not restricted to Old Norse and Latin. According to Online-Etymology-Dictionary, all across Europe, words for 'happy' at first meant 'lucky'. Perhaps this conflation originates in an ancient time when life for most consisted primarily of hardships relating to mere survival, punctuated by frequent solicitations to deities for reprieve (McMahon, 2006, pp. 2-6). In such a context happiness would have equated less to say an idyllic island holiday, significant job promotion, or new iPhone than it would have to a gift from the gods in the form of a successful hunt for a starving family, or a childbirth that did not result in death for either the mother or newborn. In a time when mere survival was life's most pressing concern and superstitious reasoning dominated, luck, chance and happiness would have been unitary.

Broad social and intellectual changes arising from the Enlightenment agitated a shift from deity-based everyday causal explanations to more scientific ones. This must surely have been the impetus to differentiate the concepts conveyed by 'happiness', 'chance' and 'luck' into different lexical forms. The shared etymology of chance and luck suggests strongly that they are inextricably linked to causal interpretation: the former being agnostic as to the underlying mechanism, the later being belief-based. But despite an Enlightenment and a manifest increase in living conditions (for much of the developed world), the conflation of luck, chance, and happiness persists today, as evidenced in the phrase, "happy-go-lucky," meaning carefree or untroubled. Prominent modern uses of 'luck' and luck derivatives bear this out more fully.

1. INTRODUCTION

Consider the use of the term in Ed Morrow's news address salutation, "Good night and good luck." This phrase originated among Londoners during the nightly German bombing raids of WWII, and was adopted by Morrow in 1940 at the conclusion of one of his London-based radio news segments. So, to say "good luck" in this context was a poignant recognition of the perils of wartime, and a heartfelt expression of hope that the well-being of a friend or neighbour be safeguarded through the night. More commonly today, "good luck" may mean nothing more than 'best wishes' as a closing to a conversation.

Consider also the use of the term 'lucky' in the Dr. Seuss book, *Did I Ever Tell You How Lucky You Are?* The old man from the desert of Drize counsels: "You ought to be thankful, a whole heaping lot, for the places and people you're lucky you're not!" He then recounts some of those who are less fortunate such as 'poor Harry Haddow' who, "Try as he will, he can't make any shadow!" In this case, 'being lucky' is very clearly equated with 'being fortunate'.

Benjamin Franklin is quoted as saying "Diligence is the mother of good luck" using the term in much the same way as Sun Tzu almost 2,500 years before. This is a common conception, luck being serendipity. In this usage, 'luck' conveys the sense that directed effort can have unforeseen, but unsurprising rewards. Penicillin, LSD, X-rays, and many other notable discoveries are commonly considered to have been the product of this sort of serendipity-luck.

'Luck' or variants of the word can take on a number of colloquial uses, as illustrated in a quote widely attributed to Sir Richard Branson: "With the casino and the beds, our passengers will have at least two ways to get lucky on one of our flights." These 'two ways to get lucky' have in common a sense of accomplishing a desired outcome in the face of uncertain odds.

There are many other uses of the term 'luck', an exposition of which is not required to conclude that 'luck' is polysemic (that is, it has a number of different meanings). Two passages from Cohen (1960) summarise the origins and modern day use of the word 'luck':

> From the beginning of its development in the Palaeolithic age, language bears the imprint of probability, in giving expression to the indefiniteness

> of perceptual and intellectual processes and in reflecting the blurred categories of things and events. ... [A] vigorous belief in luck ... [is] the antidote invented by man to help him in coping with the inescapable uncertainties of daily existence. (p. 189)
>
> The idea of luck is ubiquitous but by no means simple, in the sense that it means precisely the same to everyone, everywhere. Expressions for 'luck' in different languages introduce nuances that are difficult, if not impossible, to capture in any particular tongue. And even those who speak the same language do not necessarily use the word 'luck' in the same sense. (p. 114)

1.3 What is Luck?

Given the ubiquity of the idea of luck, and the many different uses of the term, declaring a modern-day definition of luck is no small undertaking. Barrett (2006) provides an extended discourse of elaborated stories to demonstrate the difficulty of defining luck. Here is but a sample:

> Jack works at the World Trade Centre. Or he's a tourist, or he's seeing a stockbroker—it doesn't matter how often he goes to the WTC, or his reason, as long as he intends to be there early on September 11, 2001. Now, it happens that the previous evening Jack's friend Bill slipped on a banana peel near a busy intersection in Brooklyn, and was run over and suffered a broken leg. The following morning, instead of going to the WTC as planned, Jack visited Bill at a Brooklyn hospital. Jack was lucky that Bill was run over. Bill was unlucky. But Bill was also lucky—he'd planned to go with Jack to the WTC.

Barrett (2006, p. 85) eventually proposes a succinct definition: "Luck is the impact of events beyond our capacity to rationally predict or to influence." This definition is problematic for a few reasons, the most prominent of which is that it focuses on outcomes, rather than the process that generates the outcome. In its focus on outcomes, this definition is aligned with the philosophical literature on luck.

Three types of luck, *moral*, *epistemic*, and *luck simpliciter* are reviewed in Pritchard & Smith (2004), a well-rounded treatment of both philosophical and psychological research on luck. Both moral and epistemic luck focus on outcomes that arise from chance, and are found throughout philosophical commentary on luck. Moral luck is sometimes illustrated by comparison of two agents, both having engaged in drink driving. The first agent has an accident, killing a pedestrian who stepped into traffic with insufficient warning for even a sober driver to avoid. The second agent has no accident and harms no one. A charge of manslaughter befalls the first agent, whereas only a hangover befalls the second. Several philosophical questions present, pertaining to punishment, responsibility, and agency in a world of chance outcomes. Epistemic luck is similarly focused on outcomes, in the domain of knowledge. Simply put, epistemic luck is a 'lucky guess'. The philosophical questions that present (unsurprisingly) pertain to epistemological considerations, that is, 'How do we know that we know?'

Luck simpliciter (variously referred to in Pritchard & Smith as 'quotidian luck' or 'just plain ole luck') is the type of luck of interest in the domain of psychological enquiry. The psychological literature tends to have two foci: the conditions under which a particular outcome might be attributed to luck (i.e., luck attribution; Why did my favourite team lose?); and the stable beliefs that lay people hold regarding luck as a force (i.e., luck beliefs). Pritchard & Smith assert that a singular definition of luck that can "accommodate the broad range of issues that have emerged in the psychological and philosophical literature (p. 26)" has yet to be established, and "the work of both disciplines. . . has been hampered by a failure to be clearer about what luck involves (p. 1)."

Moral luck, epistemic luck and luck attribution have in common a recognition that an outcome can arise from chance, yet nevertheless have a significant impact, either positive or negative. That impact may be on health or well-being, but also in luck attribution, on thoughts that might influence decision making or mental state. It is perhaps the idea that a non-causal force gives rise to potentially very large consequences that renders an integrating definition of luck so elusive. In the words of Wagenaar & Keren (1988, p. 65), "Few ideas are so deeply engraved in our minds as the notion that events have their causes."

A definition that captures the intrinsic essence of luck as something distinct from chance would, from a scientific standpoint, contain a paradox. So it is that a definition that does not take luck beliefs into account shifts focus from mechanism toward outcomes; chance is assigned to the mechanism either implicitly or explicitly. But assigning chance to the mechanism that generates luck outcomes neutralises the impact that an irrational belief about luck as a causal mechanism might have on decision making. Without the element of luck-as-mechanism, the study of luck in decision making is limited to the states arising from past events; it cannot include the future-oriented thoughts that impact on the calibration of probabilities.

This focus on luck as an outcome is insufficient for the present purposes. A study of the impact of lucky feelings on decision making must somehow recognise that luck is viewed as a force in the minds of some people. A study of lucky feelings is therefore a logical outgrowth of the study of luck beliefs. Darke & Freedman (1997a, p. 486) explain: " Some individuals maintain an irrational view of luck as a somewhat stable force that tends to influence events in their own favor..." Note however that a definition arising from the area of luck beliefs—a somewhat stable force that tends to influence events—is obviously problematic in application to considerations of moral luck, epistemic luck and luck attribution. Not least of all because this definition inheres an irrational belief, but also because it is focused on the process that gives rise to outcomes, and not the outcomes per se. Perhaps most problematic is the implied stability. Moral luck, epistemic luck and luck attribution all eschew stability or systematicity in the outcomes equated as lucky or unlucky, precisely because luck is driven by chance in those conceptualisations.

Because luck beliefs vary by person, a definition of luck as a somewhat stable force is by necessity not inclusive of all beliefs. Some people believe that luck is nothing more than chance, and yet nevertheless attribute a chance outcome to luck, leading to a circularity that confounds a definition: luck is chance. Others may believe that luck is a somewhat stable force, but its workings can't be known in advance, equating luck and chance by outcome but differentiating the (unknowable) algorithm that gives rise to the outcome. This again leads to a circularity that confounds definition: luck is not chance, but the patterns of outcomes are not distinguishable.

These considerations point to the reliance of an operational definition of luck, tailored for the purposes of the thesis herein. This runs the risk of a tautological definition, for example, luck is what luck believers say it is. Nevertheless, a formal, though operational, definition of luck is required that takes into account the various luck beliefs and will serve the thesis throughout. Any such definition must clarify that luck is a view, a belief held in the absence of direct observation of the workings of luck. Indeed, for some, luck is conjured into existence in the mind through an irrational belief or set of assumptions. It is perhaps this irrationality that imparts such interest to the core question of this thesis. In such 'irrationality' terms, a restatement of the question would be: In what manner (how) and to what degree (how much) does the irrational belief in luck influence decisions through lucky feelings?

Returning to the definition of Barrett (2006), "Luck is the impact of events beyond our capacity to rationally predict or to influence," a final observation is in order, already alluded to above. There is a conflict between the lucky feeling related to Barrett's focus on the impact of an event (i.e., Jack's lucky feeling) and the lucky feeling that informs risk judgements in prospective decision making. In the outcome-focused definition, the lack of capacity to rationally predict an outcome gives rise to the lucky feelings. However, the 'lucky feeling' that is of interest in this thesis serves to provide a perceived narrowing of the range of possibilities of an outcome that has yet to occur. The 'lucky feeling' in which I'm interested, lends the decision maker an increased confidence about the likelihood of an outcome. Note the direct opposition of this type of lucky feeling to any lucky feeling arising from the type of luck Barrett describes. For Barrett luck originates from surprise. For me, luck provides relative certainty.

It is reasonable that Jack, the character in the illustration above, would *feel lucky*, meaning that Jack should be thankful that he didn't experience a tragic end on 11 September 2001. In this illustration, the unpredictable and tragic destruction of the World Trade Center is a cue for how Jack should feel. But, it is also reasonable to expect that most people would find Jack's experience of 11 September 2001 to be irrelevant to whether or not he would make a risky investment or take on a risky project. (More likely, Jack would probably not be making any decisions that day, instead he might be preoccupied with how in future he can avoid entering iconic structures in major cities.)

Consider another illustration. Jill strolls to the nearby pub after work on a Friday to meet some friends. Jill had a wonderful week, a co-worker—Bill—has been absent, having slipped on a banana peel and suffered a broken leg. She's sorry for Bill, especially because this has happened to him once before she recalls (unlucky Bill). But Jill has enjoyed Bill's absence because he vociferously disagreed with her approach to a large project due this week. Jill learns from one of her friends that there is a raffle on at the pub. Perhaps she's reflecting on what a wonderful week she had because of Bill's misfortune, or perhaps Jill thinks of herself as a person for whom luck often brings good things, Jill decides to buy a ticket, thinking, *I feel lucky*. What does Jill's feeling imply about luck?

Defining luck as an irrational belief is confounded by the different types of luck beliefs that have been identified. There are at least three (introduced in Section 1.5), not including concepts such as opportunity, serendipity, fate, superstition, and the like. So a luck belief-based definition must be flexible or inclusive of different types of beliefs, described below in detail. For the moment however, based on the above discussion, I propose the following definition:

> Luck is the imagined force that actively acts to alter outcome probabilities that are otherwise known from observable causal mechanisms such as skill or control, as well as random chance. This imagined force may be viewed to alter an outcome to either the advantage or disadvantage of an individual personally or some referent individual.

1.4 Luck Attribution

Generally speaking, attributions help individuals make sense of the world around them. An attribution helps to categorise observations and direct future action: Is the person running toward me angry, scared, or exercising? If she is angry, I might get back in my car and lock the door. If she is scared, I might offer to call for help. If however, she is dressed in athletic clothes and not looking in my direction, I might just ignore her. Attributions extend beyond interpersonal agents, to processes and mechanisms, potentially providing individuals with an understanding of cause and therefore prediction. Luck can be attributed to prior outcomes, but the polysemic nature of the word 'luck' can result in confusion as to what exactly is being attributed.

To say that someone is 'lucky' can employ the term as a synonym of 'fortunate', expressing gratitude in the recognition that the outcome of some situation, decision, or endeavour was not certain to occur. A statement such as "It was lucky he found his keys in the snow" implies such a usage. In regards to negative outcomes, the word 'unlucky' can take the meaning 'unfortunate', as in "It was unlucky he lost his keys in the snow." However, for some a luck attribution may also inhere a view that luck operates as a deterministic force. As such, finding keys in the snow might signify that one 'has' luck at that very moment and so would riskier choices than normal are warranted. Similarly, losing keys in the snow might lead to the conclusion that risks should be avoided.

The distinction between luck and fortune is treated in some depth in Pritchard & Smith (2004). In a discussion of previous findings that agents ascribe luck to certain permanent life situations such as having a 'wonderful family' (Teigen, 1996, 1997), Pritchard & Smith (2004, p. 24) assert that:

> ...the agents are simply confusing luck and fortune. If it is not at all 'chancy' that one has a wonderful family, then it is not a matter of luck that this outcome occurred. Nevertheless, one might consider oneself fortunate in that one's life has developed in this advantageous fashion rather than in some other way (just as one could be fortunate, but not thereby lucky, in being born with a happy temperament).

This is the same observation from Darke & Freedman (1997a, p. 499):

> Many people will say that life has been good to them—they have better-than-average families, health, economic situations, personal characteristics, talents, and so on. This is sometimes called being fortunate or having good fortune, but is also often called being lucky.

The question of whether the past should be used to predict the future rests at the core of this distinction between lucky as merely fortunate given the circumstances and lucky as enchanted as signified by the prior outcome. From a causal attribution perspective, the word 'luck' is *antilogous*[1]. The usage of 'luck' to convey 'fortunate' implies chance played large part in the outcome, and so the outcome could not have been predicted because there was no systematic causal force. On the other hand, the usage of 'luck' to convey relative certainty about a future outcome implies an awareness of a systematic force that assists in the prediction of a future event. 'Luck' is antilogous regarding the extent to which a causal force is systematic, and is also therefore antilogous regarding the usefulness in prediction of an outcome.

[1] An antilogy, also sometimes called a contranym, enantiodrome or self-antonym, is a single word with two opposite meanings. For example: 'fast' can mean either anchored or moving quickly; 'oversight' can mean either to monitor or not notice; and 'screen' can mean either to show or to hide.

'Lucky' can also summarise multiple instances when an individual has appeared to experience positive outcomes above the rate that would be expected in the normal course of events. In this usage, there is a quality of person-centric, or person-owned, luck. A statement such as "She is lucky at two-up[1]" implies a rate of winning that deviates substantially from 50%. As before, aggregated negative outcomes can be summarised also: "She is unlucky at two-up". It is plausible that this person-luck assignment carries a greater sense of lucky as enchanted, versus lucky as merely fortunate. A luck attribution can range from personal to impersonal, changing in meaning as it moves across the range. Imagine that you personally have decided to renovate part of your house. Upon lifting the floorboards, you are pleasantly surprised to find that a previous owner hid some antique treasure there, a box of 15th century gold coins. (To absolve you of the dilemma of whether to attempt to return the treasure, assume the previous owner is no longer living and had no heirs.) A luck attribution in this case inheres some acknowledgement of chance. You bought *that* house, when you could have bought *any* house. You decided to renovate *that* part of the house, when you were considering some *other* part of the house. The previous owner decided to bury the treasure exactly *there*, although it could have been stored *anywhere*. When made regarding a personally meaningful event, the luck attribution inheres a sense of being fortunate and acknowledges that an unpredictable confluence of events gave rise to a unique outcome.

Imagine now that you are merely reading a news article about someone in a far-distant location having found this same treasure, by the same means. You might say the finder is lucky, meaning more dispassionately that the finder benefited from chance, given that: people renovate houses; sometimes houses contain hidden treasures; and it's a big world with lots of houses. It probably happens with some regularity in fact that a house-renovator chances upon some house-hidden treasure. When made regarding an event that has no personal meaning, a luck attribution still inheres a sense of fortunate-ness, but the confluence of events in the aggregate of society seems more predictable. A luck attribution that is more personal is likely to be more meaningful.

The influence on decision making that arises from an attribution to luck is likely greater when an outcome is personally relevant or otherwise interpreted in an ego-centric manner. (Winning the lottery is personally relevant; 'Saturn transiting the Sun'

[1]Two-up is an iconic Australian game involving the toss of a fair coin.

and other astrological events are arguably less so, but nevertheless egocentrically interpreted by some.) A luck attribution may give rise to the view that one is momentarily enchanted and can, or should, take greater risks than normal. Attributions to luck for a streak of outcomes may give rise to the view that possession or ownership of that enchantment is more enduring and personal. However, an attribution to luck may merely mean fortunate given the circumstances.

1.5 Luck Beliefs

There can be no direct observation of the origin, presence, or operation of a mechanism that putatively results in luck. The measurement of luck is restricted to outcomes only. Thus, the existence of an actual mechanism that gives rise to luck is necessarily a matter of belief. As already alluded to, there can be individual differences in the extent to which a person views luck as arising from a valid causal mechanism.

Belief in luck is multi-dimensional and continuous in nature. There are three compelling dimensions proposed in extant literature (Maltby, Day, Gill, Colley & Wood, 2008). A general belief in luck (GBL) asserts that luck exists and exerts an influence in the lives of most, if not all, people. A belief in personal good luck (PGL) asserts that one personally experiences favourable or positive outcomes to a greater extent or more consistently than some comparison group. A belief in personal bad luck (PBL) asserts that one personally experiences unfavourable or negative outcomes to a greater extent or more consistently than some comparison group. Any of these beliefs can vary from non-existent to strong; in other words they are continuous in nature.

A belief in luck puts the onus on an individual to be aware of its presence as an opportunity, and to 'take advantage' of a moment when luck is present. Wagenaar & Keren (1988) reports on interviews with gamblers who indicated that one can "... fail to utilize it [luck] when it happens, for instance by not even noticing ... [a] lucky day, ... lucky deck, or ... lucky dealer" (p. 66). For those who believe in luck, decision making in a world filled with uncertainty may focus attention on signals of impending good and bad luck. These signals might be experiences or outcomes, or alternatively some other environmental features related to luck, such as a favourable horoscope.

Common for both the luck-believing and luck-sceptic decision maker is that the environment—which can be seen to include past experiences and outcomes—presents information that can be drawn upon to perceive opportunities and threats. These opportunities and threats may be positioned, either implicitly or explicitly, along a continuum of probability. Decisions are made and actions taken partly on the basis of probability-calibrated perceived opportunities and threats. Of course, many distortions occur in the perceiving, in the calibrating, and in the deciding. Luck beliefs are yet another distortion to add to the long list.

Luck beliefs can be seen in general as having the potential for moderating what is perceived in the environment and the actions that are taken in response. Belief in luck can be expected to influence the extent to which a luck signal in the environment indicates that a given action is either warranted or unwarranted. This is most likely via some effect on probability-calibration.

How did an inarguably non-rational belief originate and persist, with independent emergence of luck beliefs across very different peoples over several thousand years? Perhaps a belief in luck is adaptive, at least in some circumstances. A belief in luck might encourage repeated attempts after (non-fatal) failed endeavours at some task involving both skill and chance. Repeated attempts could hone skills through practice or could lead to accidental discovery of valid mechanisms. The effect of luck belief in terms of survival or advancement must surely be contingent on the domain where the luck belief is enacted. Believing in luck at a casino is, according to probability, maladaptive in the long-run and could lead to dire outcomes such as bankruptcy. Believing in luck when soliciting investment funds for a start-up may result in persistence or confidence, which can contribute to successful outcomes.

Luck belief may also be an adaptive value for society as a whole. Heuristics that lead to decision making biases at the individual level have been demonstrated to have an adaptive value at the group level (Burns, 2004). Consider modern-day entrepreneurs. It is well known that a large proportion of new businesses fail, and thus entering into these ventures is risky. Entrepreneurs risk losing life savings, families, social standing, and even going into bankruptcy or an extended period of indebtedness. To the extent that the entry decision is affected by a belief in luck, that risk might be underestimated and maladaptive for the individual. Yet, despite the irrational individual risk, society at large can benefit from the resulting new business or technology.

A belief in luck could be epiphenomenal to misperceptions of randomness. Humans are limited in the extent to which we accurately perceive randomness, usually underestimating the extent to which a random output will contain patterns by chance (Bressan, 2002). Seeing patterns where they do not in fact exist, coupled with absence of plausible mechanism can give rise to attributions to luck. A person could accrue attributions to luck to the point that a belief in luck develops. Of course, cultural memes endorsing a belief in luck would exacerbate development of a belief in luck.

Some evidence exists to support this argument. Believers in the paranormal have been empirically shown to perceive patterns in random noise to a greater extent than non-believers (Blackmore & Moore, 1994; Brugger, Regard, Landis, Cook, Krebs & Niederberger, 1993). Believers also exhibit lower evidentiary requirements to conclude causation (Brugger & Graves, 1997).

Luck beliefs are probably quite stable within a person as they are probably based in part on past experiences, but also on cultural influences. Luck beliefs may alter the calibration of probabilities of a given outcome. Luck beliefs are likely to act as a moderator of environmental signals (perceived to be related to luck) and decisions involving risk.

Luck beliefs will be addressed in depth in Chapter 3 where a scale is validated for use throughout the remainder of the thesis.

1.6 Lucky Feelings

In May 2011, the Google search pages (globally) received over *a billion* unique visitors comScore (2011). The Google search page is famously spare of content, yet contains a second search button labelled “I’m feeling lucky.” At least for Google, there appears to be a common understanding of what is meant by feeling lucky.

“Feeling lucky”, as used on the Google search page, communicates a positive expectancy about an uncertain outcome. This is indicated by the functionality of Google’s “I’m feeling lucky” button. It directs users to the first webpage returned for a given query, bypassing the usual listing of ordered search returns. There is however an alternate meaning of “feeling lucky”, that of gratitude. Having survived a plane crash, one might say “I feel lucky”, in which case an assessment of something that has already occurred is held prominently in mind. These are merely inferential definitions though. The purposes of the present work require a greater degree of precision as regards lucky feelings. Lucky feelings are central to the primary research question. Ambiguity in what is meant by 'lucky feelings' may hinder attempts to explore that question.

I take three broad approaches to delineating lucky feelings below. The first approach explores meaning in the context of everyday use, a semantic approach. A second approach explicates the phenomenology of lucky feelings. By phenomenology, I refer to the physical sensation and cognitive experience of lucky feelings. Finally, I consider the factors that might give rise to lucky feelings.

1.6.1 Semantic Approach

On January 8, 2011, Matthew Laos attended a "Congress on your Corner" event to meet US Congresswoman Gabrielle Giffords. Only minutes after he left the event, a disgruntled citizen fired on the crowd, attempting to assassinate Giffords. Six people died and thirteen were wounded. Mr. Laos had missed the shooting by mere moments, reporting the sound of fireworks in the distance as he departed. He later commented to a local reporter: "I'm so lucky that I wasn't there just that moment. I just can't believe that I missed it, yes, I feel lucky."

Here, to feel lucky conveys gratitude, a sense of thankfulness. Of course, one can also feel despair, as in "I feel so unlucky—My uninsured car was just stolen!" Note that lucky-gratitude and lucky-despair might usually be followed by "that . . . " or otherwise imply some reference to the origin of the gratitude or despair. Note also that it these gratitude and despair statements are retrospective, taking into account what both has happened and what *did not* happen. Mr. Laos feels lucky-gratitude for leaving a moment before the shots were fired. Had he *not* done so, he could have been shot to death.

The comparison of an actual outcome to a counterfactual alternative appears to be a very important component of luck attributions and lucky feelings associated with gratitude or despair. These counterfactuals represent the gap between what was expected and what was experienced. The role of counterfactuals in cognitions involving luck has been examined previously both theoretically and empirically. It is a topic that receives extensive treatment throughout this thesis.

Consider now a quite different usage of 'lucky feelings'. In 2007, Lucretia Ott explained her decision to purchase what was to be a winning Kansas lottery ticket: "I purchased a soda from a pop machine and it gave me two. I then bought one bag of chips from a vending machine and it gave me two. I felt lucky, so I bought lottery tickets." Here, to feel lucky connotes an optimism; an expectation of future success. Conversely one might say, "I feel unlucky today, I think I'll slow the car down", connoting a pessimism. Note that lucky and unlucky might usually be followed by "so, . . . ", or otherwise imply some future action to take as a result of the lucky feeling. In this way, lucky feelings inhere a prospective element. These prospectively oriented lucky feelings are at the core of the research question addressed herein.

At first inspection, differentiating lucky feelings on the basis of retrospective versus prospective seems promising. However, closer scrutiny reveals that the distinction between the two types of lucky feelings may be somewhat precarious. Note that a 'prospective lucky feeling' would normally be expected to arise from some experienced event. For example, Ms. Ott received two bags of chips and two drinks. In this respect then, a 'prospective lucky feeling' is based on a retrospective account, and is slightly confusing. A further differentiation that takes into account the focus of the lucky feeling is helpful to resolve this confusion. The core element of what I've referred to above as a 'retrospective type' of lucky feeling is the feeling is concerned with well-being. The core element of what I've referred to above as the 'prospective type' of lucky feeling is that the feeling is concerned with expectancy.

Ortony, Clore & Collins (1988) propose a global structure of emotion types, categorising basic emotions into different families. Though they do not specifically discuss lucky feelings, they explain that ". . . the well-being emotions result from focusing attention on the events themselves rather than on events as tempered by the *prospect* of their occurring" (p. 85; c.f. Fig 2.1 on p. 19). It is the assessment of the past outcomes that drives the well-being associated emotions, such as gratitude and distress. *Prospect* emotions relate to unconfirmed event outcomes and arise from the thinking about what might happen; what could eventuate. According to Ortony et al. (1988), hope and fear characterise these prospect types of emotions. A unique feature of lucky feelings, is that they are likely to arise from past events, but have a focus on future events. There is some kind of appraisal of a previous outcome or set of outcomes that then feeds forward to the appraisal of future unconfirmed outcomes.

For the purposes at hand, I will retain the labels of 'retrospective' and 'prospective' to denote the two types of lucky feelings, as these terms are slightly less unwieldy than alternatives. This is done though, keeping in mind the assignment of these to well-being and prospect categories set out in Ortony et al. (1988). My interests in this thesis focus on the influence of expectancy oriented lucky feelings on decision making involving risk, and not on well-being, gratitude or distress *per se*. Nevertheless, lucky feelings may not be so readily separable in the mind of a decision maker. A person could feel both lucky-retrospective as well as lucky-prospective, at having survived a car accident that for all accounts should have been fatal. While that person might slow down at the crash site next time she drives past, she might also buy a lottery ticket at the next opportunity (or decide to engage in some other risky endeavour like start a business, get married, have a child, or change jobs). So, these two types of lucky feelings can overlap and arise from the same event. These two types of lucky feelings may also interact. A well-being lucky feeling could influence an expectancy lucky feeling, and vice versa.

Like retrospective-lucky feelings, there may also be an element of counterfactual thinking involved in prospective-lucky feelings. Ms. Ott's presumption was that she would receive one pop and one bag of chips. That presumption was violated when she received two of each, and that counterfactual formed the basis of her expectancy oriented lucky feeling. The counterfactual reasoning differs across the two types of lucky feelings in one important way. For both, what factually occurred was anomalous. Moreover, for both the counterfactual represents a worse outcome. But for a retrospective-lucky feeling, there is an implication that the counterfactual was in some way negative or undesirable in an absolute sense. For the prospective-lucky feeling, there is an implication that the counterfactual was in some way normal or acceptable. Take for example the retrospective-lucky feeling of a parent who narrowly catches a young child running into a busy street. The counterfactually worse situation is inconceivably disastrous. Contrast this with the counterfactual implied in the statements by Ms. Ott. The counterfactual is wholly acceptable, a single soda and bag of chips, as advertised on the vending machine. Had the counterfactual not been acceptable, Ms. Ott would not have engaged in the purchase of the snacks in the first place.

Are prospective-lucky feelings relevant only for purchases of lottery tickets or similarly small stakes? Even small effects can have large consequences, when they occur at the margin. Prospective-lucky feelings may fall into this category. If, in appraising some prospect, there is a fine balance between those factors that argue for and against some course of action, prospective-lucky feelings might adjudicate the decision. Prospective-lucky feelings are probably more influential for immediate and inherently subjective decisions, as compared to protracted decisions and decisions which appeal to more objective assessment. This is not to say though, that decisions involving high stakes would not be influenced by prospective-lucky feelings. Consider a recent graduate who has been offered a job and must decide with haste because of financial pressure and a short deadline. This is an important decision, probably with far-reaching consequences. The graduate might turn down the job offer in anticipation of a better one from another possible employer, based partly on feeling prospective-lucky. (Or alternatively, accept the job offer, based partly on feeling unlucky.) One only has to alter Ms. Ott's statement above slightly to effect such a sentiment: "I felt lucky, so I decided to wait."

Note that in the above illustration of the job-seeker, the inseparability of the two types of lucky feelings is suggested. Turning down the first job offer might be explained as feeling lucky, but whether this prospective-lucky feelings, retrospective-lucky feelings or both is probably not clear in the individual's mind. If this hypothetical decision maker feels fortunate to be living at home with parents who provide meals, use of the car, and an allowance, then a positive expectancy about the next application is probably at least due in part to well-being.

In summary, there appear to be two primary semantic uses of variants of 'lucky feelings'. Conceptually the two types of lucky feelings are readily separable. The first, retrospective-lucky feelings, relates an individual's present state of being to some events that have occurred in the past. Associated terms used for 'lucky' in this sense are gratitude, or in the case of unlucky feelings, distress. The second, prospective-lucky feelings, relates an individual's present state of being to a future uncertain outcome or event. Associated terms for 'lucky' in this sense are hope, or in the case of unlucky feelings, fear.

1.6.2 Phenomenological Approach

Putting aside well-being oriented lucky feelings, what do expectancy oriented lucky feelings *feel like*? On the one hand, this type of feeling lucky appears to be associated with calm reassurance in much the same way that a confident performer might experience those moments before a familiar recital. On the other hand, feeling lucky does not reflect the same calm reassurance that results from knowing the smoke detectors in one's home have fresh batteries. Feeling lucky carries with it a sense of purpose, a heightened state of arousal. In this way, feeling lucky is not only a feeling of optimism, but also has an element of vigilance and flutter of excitement.

Feeling unlucky has a similar complexity. On the one hand, feeling unlucky appears to be associated with a gloomy outlook. On the other hand, if one feels prospectively unlucky then no commitment has been made to engage in risk. As such, there may be a feeling of relief. That relief may be tainted however, by the thought that by not taking a risk, some opportunity may be lost. In this way, feeling unlucky is not only a feeling of pessimism, but also has an element of surety mixed with resignation.

Lucky feelings are a complex mixture of cognitions and embodied states. These embodied states may be referred to as moods, emotions and affect[1]. These terms are somewhat challenging to precisely define, and accordingly are subject to a degree of disagreement among researchers in those areas. The exact assignment of lucky feelings to one or more is not needed here, but some basic boundaries for the terms may be helpful.

A *mood* is a relatively diffuse and enduring state, capturing a prevailing tone or attitude. Some words that might describe a mood are 'good', 'bad', 'critical', 'receptive', 'engaged', or 'detached'. There may be minimal influence on mood from conscious prior experiences, and so cognitive appraisal is less active in giving rise to moods. An *emotion* is more directed, intense and brief. Emotions arise in reaction to (appraisals of) thoughts, experiences, and events. There is a large lexicon of emotion states. Some words that describe an emotion are 'joyful', 'happy', 'angry', 'sorrowful', 'embarrassed', or 'tense'. *Affect* is a composite of emotions, usually measured by several emotion words that vary in two dimensions: valence and activation. Valence can range from positive to negative. Activation can range from active to passive. Usually affect is denoted as simply positive or negative. Moods can also be thought of as elemental to affect.

The obvious question then emerges, what is a 'feeling'? At the risk of infinite regress, it may be useful to place lucky feelings in the context of moods, emotions and affect. Feelings are most closely related to emotions as described above. A feeling though, implies a degree of perception that is readily accessed in subjective conscious: one can 'feel' the warmth of a fire (haptic perception); one can 'feel' hunger (interoperception); one can 'feel' they are seated with a particular posture (proprioperception).

[1] See Forgas (1995, p. 41) for a well-referenced explication of these three terms.

For the present purposes, a feeling, as relates to a lucky feeling, is the subjective conscious experience of both the bodily state and the content of thoughts. A feeling is often used as a summation of an individual's experience relative to a stimulus. (That stimulus may include a personal thought or distant memory.) A feeling is subject to explicit interpretation despite there being questionable lexical sufficiency to convey the precise feeling.

The *Somatic Markers Hypothesis* (Damasio, 1994) describes a process of decision making that relies partly on emotion, partly on cognition, and partly on biological 'markers'. These markers—which may include heart rate, blood pressure, muscle tone, and a number of other internal physical correlates—provide information to the brain about the subconscious interpretation of stimuli. For a decision maker with limited working memory, the more powerful cortical processes push information to near consciousness via the physical body. Results from a study in Wagar & Dixon (2006) provide an empirical illustration. Study participants' galvanic skin response preceded an increase in the drawing of cards from the higher payout deck in the Iowa Gambling Task.

Another theoretical account, that of Loewenstein, Weber, Hsee & Welch (2001), provides a less biologically-specified explanation of the importance of affect and emotion in decision making. In this *Risk-as-Feelings* account, cognitive evaluations and feelings[1] have a bi-directional influence on one another, and each make a contribution to a decision or behaviour. Cognitive evaluation is limited to anticipated outcomes and subjective probabilities. These also drive feelings, but a third category of influences of feelings is proposed: "Other factors". These factors relate to mood, affect, the immediacy of the situation, vividness, and a number of others. The common feature of these other factors is that are not amenable to a rational utility-weighted calculus.

There is a substantial volume of work on the role of emotion in decision making that casts cognition and emotion as complementary and not antagonistic (Clore & Huntsinger, 2007). The affect-as-information hypothesis proposes that emotions give rise to affect, and that affect provides information about some target or decision Clore, Wyer, Dienes, Gasper, Gohm & Isbell (2001). Others have termed this the "affect heuristic" (Finucane, Alhakami, Slovic & Johnson, 2000). An alternative theory in the same domain is the Affect Infusion Model. This model integrates mood with decision making

[1]Emotion and feeling are conflated without distinction in Loewenstein et al. (2001).

(Forgas, 1995), asserting that as complexity of a situation or decision increases, cognitive load increases, resulting in a compensatory influence of mood. The general thrust of research in each of these areas is that a decision maker can draw on mood, emotion, and affect to answer the question, “How do I feel about this?” That feeling may arise from environmental cues or personal thoughts and vary in the degree to which an individual is consciously aware of its origin.

A personal thought, stimulated by apparently nothing or at least from a source beyond awareness, can alter one’s mood or lead to some emotion and result in an affective state or experience. So, thoughts can lead to moods, emotions and affect, and these can alter thoughts. This chain reaction can happen with more or less conscious awareness, giving rise to a judgement regarding how one feels with respect to a target. States of being that result from this interplay of feelings and cognition are complex, and can be described as an affective-cognitive (Clore, Ortony & Foss, 1987).

Lucky feelings are most certainly affective-cognitive. On the cognitive side of the ledger, lucky feelings can originate from cortical processes such as basic perception as well as higher order processes such as memory, representation, and computation. On the affective side of the ledger, palpable interoceptive or somatic responses might result from the risk inherent to the upcoming decision. The situations in which lucky feelings arise present uncertainty and so are cognitively demanding. The affect infusion model would therefore predict that decisions are more influenced by the embodied state. Lucky feelings may provide information to cognition, but may also be the result of cognition. This interplay would result in a further complexity.

In summary, a prospectively oriented lucky feeling is a relatively brief affective-cognitive state that is consciously accessible and may be relied upon to inform decision making in a heuristic manner, either explicitly or implicitly. A lucky feeling reflects the whole experience of physiological embodiment of emotions as well as cognitive content. The emotions and cognitive content that give rise to a lucky feeling may have recursive influences and complex interactions. At a fundamental level, a lucky feeling provides the luck-believing decision maker with information that might alter calibration of outcome probabilities.

1.6.3 Factors Leading to Lucky Feelings

Usually a lucky feeling is relevant for a decision or choice in the immediate future. In this way, lucky feelings might be thought to require a *raison d'être*. Alternatively, a lucky feeling may instigate a search for an outlet; a means by which to deploy the lucky feeling. That someone would feel prospectively lucky with no target, or for no reason at all, is not a compelling notion. So, loosely speaking, a decision in the immediate future could be considered a necessary but not sufficient condition for lucky feelings. A decision that has been made, but for which the outcome is unknown would qualify in this respect.

Above, I used the term 'luck-related signal' to communicate some environmental feature, personal experience or thought. There are a few categories of these signals. Before discussing those categories, it may be useful to clarify the relationship of belief in luck to lucky feelings. Recall that belief in luck is multi-dimensional and continuous for each dimension. A belief in luck may be sufficient to lead to lucky feelings directly and not as a moderator of a luck-signal.

Imagine that a person has just arrived at a bus stop. A bus approaches, that takes a circuitous route to the intended destination. There is a more direct bus scheduled at about the same time, but it could have already gone past the stop. So the choice is take the no-risk longer route or opt for a risky wait for a bus with a shorter route but that may have already run. Imagine further that the person at the bus stop has experienced no discrete luck-related signals recently. In this instance a belief that one is personally lucky might be sufficient to initiate lucky feelings. Or alternatively, a belief that one is personally unlucky might initiate unlucky feelings.

From a logical standpoint, it seems that a belief in luck is required for a person to interpret a signal as luck-related. A person might feel lucky in the absence of a signal, but the inverse is untenable: in the presence of a luck-signal an absence of a belief in luck can be expected to neutralise the luck-signal. Take for example an individual who is at the extreme end of the range of disbelief in luck, who has just plucked a four-leaf clover, or received two bags of chips having only paid for one. Without a belief in luck, a four-leaf clover is nothing more than a genetic aberration and the two bags of chips indicates a faulty machine.

There are many superstitious omens or rituals that might be interpreted as luck-signals, and give rise to lucky feelings: black cats, ladders, the number 7 or 13 (in western cultures), the number 8 or 4 (in eastern cultures), the aforementioned four-leaf clover, a horoscope, genuflecting, crossing fingers, knocking on wood and many others. There are also outcomes of personal relevance unrelated to superstition: winning or losing in a competition, winning or losing in a game of chance, auspicious events relating to coincidences (i.e., a jockey's colours matching one's shirt), experiencing a series of unlikely outcomes (i.e., getting all green lights on the way to work), having a previous risky choice turn out well, and many others.

Priming in various ways could influence lucky feelings. Examples of this might be hearing a story from a friend about how good or bad luck intervened for him, a non-conscious exposure to an image of lady luck in peripheral vision, the song *I feel lucky* by Mary Chapin Carpenter subtly playing in the background while riding an elevator. Generally speaking, priming can be conscious or unconscious. That is, there could be awareness of the priming as in the case of a friend saying, "good luck." Or the priming could be unconscious, as in the case of an experiment by Jiang, Cho & Adaval (2009) that presented the word 'lucky' on a screen for 120ms. The priming may be perceptual, as in the case of Jiang et al. (2009). Alternatively, priming could be conceptual as in the case of the study reported in Chapter 4. In that experiment participants were explicitly asked to write about a time when they were lucky.

1.7 Summary and Conclusions

In this chapter I have sought to provide an introduction to lucky feelings, and a number of related concepts. Luck concepts have been part of human thought for millennia and were spontaneously emergent across isolated cultures that predate even the Common Era. The word 'luck' has a history of conflated meanings, beginning with a lack of differentiation between lucky and happy in the 15th century, tracing to a modern-day lack of differentiation between lucky-gratitude and lucky-expectancy.

A definition of luck was proposed in Section 1.4 that moved the focus of previous conceptualisation of luck, from outcome to mechanism. Conceptualisations of luck as an outcome would imply that lucky feelings originate from unpredictable outcomes, whereas luck viewed as a mechanism implies that lucky feelings narrow the probability distribution of a future outcome. In short, luck is as an imagined force that actively acts to alter outcome probabilities.

The third section introduced the idea of luck attribution; the assignment of luck as relating to some outcome or set of outcomes. An attribution of luck may associate luck with a situation or to a set of aggregated outcomes. In the case of the later, an individual is often credited with possessing the luck to some extent, whereas in the former, luck may be seen as an essence that 'moves' according to its own designs. Luck attributions that are personal in nature are likely to have a greater effect on decision making.

Luck beliefs were introduced in Section 1.5, where three compelling dimensions are proposed: a general belief in luck, which holds that luck plays an important role in the lives of most people; a belief that one is personally lucky; and a belief that one is personally unlucky. Luck beliefs are likely to act as a moderator of environmental cues and lucky feelings. Based on pre-existing measures, Chapter 3 validates a scale—the BIGL16—for use throughout the thesis[1].

The final section, Section 1.6 took three approaches to establishing a conceptual understanding of lucky feelings. The first approach, a semantic one, examined common uses of the phrase "I feel lucky", concluding that uses of the phrase mirror the outcome-mechanism distinction. That is a lucky feeling can be retrospectively or prospectively oriented. The second approach, a phenomenological one, attempted to delineate the psycho-physical experience of a prospectively-oriented lucky feeling, describing it as a brief affective-cognitive state that might alter calibration of outcome probabilities. The third approach considered the factors giving rise to a lucky feeling, noting that lucky feelings may arise from prior events, but that in some cases, no prior event need be held saliently in mind in order for a lucky feeling to arise.

In the next chapter, I conduct a literature review that explores the boundaries of the existing understanding regarding the concepts just introduced.

[1]The BIGL16 (*16-item Belief in Good Luck Scale) contains items originally found in two earlier scales. Both of those original scales were titled "Belief in Good Luck Scale" by the respective authors. Retaining the original name for this third scale proposed herein rightfully pays homage to the developers of the scales, but it also has the potential of introducing confusion without a means of differentiating between the three scales. Thus, throughout this thesis I will append the number of items to the acronym, as follows: 'BIGL12' for the first scale; 'BIGL22' for the second scale; and 'BIGL16' for the third. The origin and composition of the three scales is comprehensively discussed in Chapter 3.*

Chapter 2

Literature Review

Chapter 1 introduced lucky feelings and related concepts. In the present chapter, I discuss previous research related to luck and establish my research aims. There are three major sections.

> **Section 2.1** establishes the framework of empirical and theoretical literature within which the research questions are posed. It aims to place the present work among a broader set of assumptions of a paradigmatic nature.
>
> **Section 2.2** details the research that has an immediate bearing on the present work. It aims to identify gaps in the current understanding of lucky feelings and their influence on decision making.
>
> **Section 2.3** develops the research questions addressed herein, and outlines the chapters to follow.

2.1 Contextual Literature

The question of luck attributions represents the majority of the psychological research on luck (André, 2006; Pritchard & Smith, 2004). In the 'luck attribution' literature, the dominant questions concern the factors that give rise to a view that luck has played a role in some outcome. The impact of luck attributions on decision making has received relatively less attention.

2.1.1 Attribution Theory

The earliest[1] relevant work combining causal reasoning and luck categorised luck as an 'environmental force' (Heider, 1958, p. 91) and noted that "... a diversity of conditions lead to the cognition of luck." Heider established the foundations for Bernard Weiner's *Attribution Theory* (Weiner, 1974; Weiner, Frieze, Kukla, Reed, Rest & Rosenbaum, 1972), which was developed with achievement motivation in mind. The theory was developed in the context of academic performance and learning in response to feedback.

According to attribution theory, there are three dimensions that form the basis for a causal interpretation of some outcome. In combination, these should ultimately explain future performance through reactions (e.g., persistence) to performance feedback (i.e., success or failure). The first dimension is internal - external: Is performance related to factors that originated within the person (i.e., ability; effort) or from the environment? The second dimension is stable - unstable: Do those factors hold constant or vary? The third dimension is controllable - uncontrollable: Can the factors be changed or influenced so as to improve performance? Luck was positioned as an external, unstable, and uncontrollable factor. This is a description of chance more so than luck. Luck may or may not be unstable, depending on the dimension to which this refers. A belief that one is personally lucky or unlucky implies stability and internality, for example.

The conceptualisation of luck in Weiner et al. (1972) and Weiner (1974) was not adopted without question. Fischhoff (1976) noted that luck and chance differed by locus, where luck was person-centric and chance had its locus in the environment. Later, Chandler & Spies (1984) makes this observation regarding usage of the term 'luck' in the original conceptualisations by Heider (1958) and Weiner et al. (1972), indicating there is confusion as to what exactly is meant by the term. Weiner himself later commented (Weiner, 1983, p. 534) that, "In studies that manipulate causal attributions, the instructional manipulation, the characteristics of the task, and the task feedback should be congruent. For example, luck instructions for a coin toss that is accompanied by a random schedule of reinforcement are most likely to be accepted and result in an ascription to chance."

[1] Of course, ancient scholars (like Polybius) were already thinking and writing about the role of chance, luck, skill and directed effect in determining outcomes. However, for relevance, I restrict my comments here to modern theoreticians and empiricists.

Contemporaneous with the work by Heider, Rotter (1966, 1954) introduced Locus of Control, which was seen as an individual difference in regards to attitude or belief about the origin of important influences in one's life. Those with an internal locus of control were thought to have a greater sense of agency in the world. Those with an external locus of control were thought to see their environment as more influential.

Several of the items in the original locus of control scale (Rotter, 1966) contain the word 'luck'. The observation of Chandler & Spies (1984) would apply equally to Rotter. Take for example, the following item: "It is not always wise to plan too far ahead because many things turn out to be a matter of luck anyway." Here, 'luck' appears to be consistent with Weiner et al.'s characterisation of an external, unstable, and uncontrollable factor. This usage of 'luck' is carried forward to later, more refined scales measuring locus of control (Levenson, 1981).

In addition to the complications that arise from the conflation of luck and chance, there is a second challenge to integrating insights from attribution theory to the present work. As well as internal or external, Weiner et al. (1972) proposes that causal factors are either stable or unstable. 'Luck' was viewed as unstable and external. Integrating the two of the three different dimensions of belief in luck with this external/unstable categorical assignment is problematic (Darke & Freedman, 1997a). To wit, a belief that one is personally lucky (or unlucky) indicates that luck is neither external nor unstable. On the contrary, these beliefs are tantamount to a view that luck is internal and stable.

The conflation of luck and chance in these lines of enquiry limit the extent to which attribution theory findings are applicable to the present work. Moreover, that conflation, two dimensions of luck beliefs violate the view of luck advocated by Weiner et al. (1972). In the attribution theory perspective, luck is an external and unstable force. However, a belief in personal good luck (PGL) and a belief in personal bad luck (PBL) both are characterised as beliefs that luck is both internal and stable.

2.1.2 Illusion of Control

Research on the Illusion of Control (Langer, 1975) adopted the framework of Weiner et al. (1972) and examined the conditions under which a person would overestimate their ability to control the uncontrollable. Often the illusion of control is seen as an ego-protective or ego-promotive reaction to outcomes generated from processes that are opaque with respect to the degree of influence owing to chance versus skill. In this view, for the person who has performed poorly, outcomes are blamed on chance processes. For the person who has performed well, outcomes are credited to skill.

However, there can also be a superstitious reasoning element to the illusion of control. That is, a superstitious reasoner may view himself or herself as having a metaphysical element of control. In this line of enquiry, luck—or perhaps more accurately a belief in personal deployment of luck—is equated with control. Wohl & Enzle (2002) integrates this superstitious-reasoning illusion of control into a study of decision making after a lucky event.

2.1.3 Common Conceptions of Luck

Cohen (1960)'s succinct work titled *Chance, Skill, and Luck* lays the foundation for a more directly applicable line of research in relation to luck. Cohen provides a historical and theoretical account of doubt and uncertainty in decision making, something he termed 'psychological probability'. Introductory pages are devoted to an overview of various ancient religious and philosophical orientations to doubt, followed by a brief treatment of doubt in the tension between science and religion during the renaissance and up to contemporary times. He highlights the replacement of fealty to capricious gods with the scientific method as a means of attempting to extract knowledge from and exerting control over an uncertain world. The impact of these broad cultural changes on cognition involving luck is obvious: luck, though still present in modern day thinking, is no longer alone in explaining outcomes. Chance and verified mechanisms represent an alternative that may be more or less valid for a given individual, depending on his or her beliefs, education, experience, peer group, cultural customs, job description, or any number of other factors.

Over the remainder of the book he "...attempts to make explicit the systematic tendencies or patterns inherent in 'guessing' and gambling activities" (p. 189). 'Guessing' here indicates decision making under conditions of uncertainty. Luck is discussed at length in the work, and one passage in particular conveys the essence of the larger work in relation to luck (p. 114):

> It would, I think, be a mistake to suppose that such notions of what will happen if we are lucky or unlucky are merely ghostly ideas or conventional formulae which have no impact on what we actually do. On the contrary,

> I suggest that all our decisions and predictions are guided or governed, implicitly if not explicitly, by what we imagine luck and unluck might bring and not merely by cold-blooded 'objective' calculations.

Although it may not be clear from this passage, as suggested by the title of his book, Cohen does not conflate luck and chance. Rather, he discusses luck in terms of belief in luck and to a limited extent, lucky feelings.

Much later, Wagenaar & Keren (1988) reported on two empirical tests of the degree to which chance and luck are distinct in the minds of 'ordinary subjects in everyday situations'. That research was inspired by interviews with gamblers that sought to explore beliefs about the role of skill and chance in gambling. The gambler-interviewees were reluctant in their responses, and indicated upon questioning that luck should be included. The two studies employed a semantic approach grounded in psychology. Study 1 participants drafted stories illustrating either luck or chance that were then rated by a different set of participants along 12 dimensions. Two discriminant functions were found for the dimension ratings, one for luck and one for chance. Two of these dimensions that loaded highest on the discriminant function, consequences and surprise, were then used to construct a set of stories for Study 2. The stories systematically altered the levels of the two dimensions. Participants rated stories by the extent to which luck (in one condition) or chance (in another condition) accounted for the event in the story. Results from Study 2 only partially agreed with Study 1. Study 1 indicated that luck was associated with consequences, and chance was associated with surprise. However, Study 2 found that surprise was also related to luck. Wagenaar & Keren (1988) concedes that although a belief in luck can in principle influence behaviour, they have not provided a critical test in their studies—rather they confirmed that chance and luck are perceived as distinct causes of events. Further research was recommended.

Karl Teigen has produced the largest volume of work in relation to everyday conceptions of luck[1]. Teigen's interests in luck appear to have grown out of a research programme focusing on subjective probability (Teigen, 1974a,b, 1983a,b,c,d, 1984). Like Wagenaar & Keren, the bulk of Teigen's work on luck is also semantic, exploring the meaning of words in relation to the interpretation of stories and phrases.

[1] Research on conceptions of luck among gamblers has attracted a lot of attention, but is mostly confined to individuals with clinically problematic behaviours, beliefs and attitudes in a pathological gambling context. This research is thus of questionable relevance for insights to everyday situations.

Teigen (1995) explored the notion that counterfactual thinking plays a key role in luck cognitions. Although counterfactual thinking is discussed in depth in Chapter 4, I provide a basic introduction now. Counterfactual thinking occurs when a person imagines an alternate outcome to reality. Several characteristics to counterfactuals have been specified, but the most important one is that of direction. A counterfactual thought, usually just abbreviated to 'counterfactual' can be either upward or downward. An upward counterfactual compares the actual outcome to an imagined one which is *better* is some important way, as exemplified by the statement, 'I almost won'. A downward counterfactual compares the actual outcome to an imagined one which is *worse* in some important way, as exemplified by the statement, 'I almost lost'. Teigen (1995) extends the work of Wagenaar & Keren (1988) using a similarly semantic approach.

In Teigen (1995)'s first study, elicited stories were rated along several dimensions. Good luck and bad luck stories were found to differ primarily in terms of the variance and range of ratings. Ratings for luck in good luck stories varied more than ratings for luck in bad luck stories, as measured by comparing standard deviations. The range of ratings for good luck stories was also greater than that of bad luck stories. In the second study, good luck and bad luck stories were again rated for attractiveness (i.e., Would you like to be involved in this story?) and 'closeness' of a counterfactual event. Closeness did not differ across good and bad luck stories, although attractiveness did. However, the degree of luck associated with a good luck story significantly correlated with counterfactual closeness (positive correlation) and counterfactual attractiveness (negative correlation). The degree of luck associated with bad luck stories was uncorrelated with both counterfactual closeness and counterfactual attractiveness. Studies three and four requested positive and negative stories, without reference to luck. Other aspects of Study 3 and 4 mostly mirrored studies one and two respectively: Study 3 showed similar findings to Study 1. Study four showed a similar pattern of results to Study 3, and compared lucky, unlucky, positive and negative stories in terms of counterfactual closeness and ratings of attractiveness of actual outcomes and counterfactual ones. Teigen (1995) summarises the results as indicating that counterfactuals matter in judgements of luck. How lucky or unlucky one judges an event is influenced less by how attractive an outcome is than it is by an awareness of how it could have been different. Teigen also underscores the differences in good and bad luck, a topic to which he returns in Teigen, Evensen, Samoilow & Vatne (1999), overviewed below.

Teigen (1996) reports six vignette-based studies that altered only the circumstances that gave rise to a given outcome. For each study, the outcomes were the same for all conditions—only the circumstances that give rise to the outcome are manipulated. In Study 1, participants rated a fictitious player in a wheel of fortune game as feeling more lucky if the wheel stopped closer to "lose". The amount of area on the wheel devoted to win and lose were the same, only the total number of win and lose sectors, and therefore also their widths, varied. Participant ratings for the probability of winning and losing were equal across conditions. In Study 2, a two-stage game was presented for two different fictitious characters in a story. The probabilities of winning in stage one and two were reversed for the characters, so that the overall probability of winning was equal for the two characters, but the lower probability stage was first for one and second for the other.

With one important addition, this study replicated the design and results of Miller & Gunasegaram (1990), which found that later stages of multi-stage decisions are seen as more mutable, mutability being the central feature of counterfactual closeness. In Teigen (1996), the character experiencing a lower probability of winning in stage two was also judged to feel more lucky. That character was also judged to be more excited after the first stage and more satisfied at having won after the second stage. The effects of winning on feeling lucky, excited and satisfied were mirrored in another set of conditions testing losing with feeling unlucky, excited and dissatisfied. The results indicate that feeling lucky and unlucky are associated with mutability of an outcome. In Study 3, the realism of the counterfactual was manipulated in the vignette, with the effect of greater realism leading to higher judgements of lucky feelings. In Study 4, choice in a decision as compared to no-choice, was demonstrated to have the effect of leading to increased judgements of lucky feelings. Study five illustrated that a second misfortune following a bad luck event can nullify unlucky feelings. Study six is of limited application to the present work.

The general conclusion from the six studies is that counterfactual thinking must be taken into account when studying lucky feelings. Rightly so, Teigen asserts that Norm Theory (Kahneman & Miller, 1986), which explains affective reactions to counterfactual thinking, extends to judgements of luck. In his own words (p. 297): "...the counterfactual alternative does not only determine *degree* of affective evaluation, but (particularly in the case of luck) also the psychological *quality* of the incident, as being a lucky rather than an unlucky one."

Teigen (1997) related luck, envy and gratitude in the context of social comparisons. He found that all three arise through counterfactuals. There was a strong focus on the meaning of luck phrases, with findings such as: 'I am lucky' indicates gratitude; and 'You are lucky' indicates envy. The results of this study are limited in their applicability to the present work, apart from suggestion that social comparison processes might be important in the generation of lucky feelings. Teigen (1998) investigates hazardous and careless situations in personally recalled stories, finding that judgements of being lucky were often associated with instances of risk taking, and that vivid counterfactuals of perilous outcomes were implicated as the mechanism.

Teigen et al. (1999) goes further into a semantic exploration of counterfactuals and luck judgements, finding across five studies that particular features of a narrative can trigger good and bad luck attributions. In Study 1, judgements of personal good and bad luck appear to be subject to priming. Recall of a personal experience in which a positive outcome was missed led to a higher judgement of being 'a person who is often unlucky'. Recall of a personal experience in which a negative outcome was avoided led to a higher judgement of being 'a person who is often lucky'. It is noteworthy that despite Darke & Freedman (1997a) assertion that belief in luck is stable, judgements of personal good and bad personal luck were demonstrated in this study to be labile to a manipulation. Wohl & Enzle (2003) also demonstrated luck beliefs to be responsive to an experimental manipulation.

In Study 2 of Teigen et al. (1999), recalled good luck stories were found to have a surprising twist at the end of the story, where something positive occurred. This finding is in agreement with Wagenaar & Keren (1988), which found surprise to be associated with luck. Recalled bad luck stories on the other hand were found to continually decline throughout the narrative. In Study 3, good luck stories spontaneously referenced close counterfactuals, and bad luck stories focused on seemingly normal initial conditions. This is in agreement with Teigen (1995), which found no correlation between story ratings of bad luck and counterfactual closeness. In Study 4, the sequence of positive and negative events in a story was altered, resulting in differing judgements of luck. Holding outcome constant, if the narrative concluded with a positive event, it was more likely to be judged a good luck story. If the narrative concluded with a negative event it was more likely to be rated as a bad luck story. Study five demonstrated that an actual outcome need not be exceptionally good for a story to be judged lucky, so long as a generated counterfactual is worse.

In a recent study, Teigen & Jensen (2011) continues research on counterfactual thinking with a study of victims of a natural disaster. Victims who survive tragic disasters although they sustain serious injury pose a curious question: What reference point will be used in the spontaneous generation of counterfactuals? Does a person consider themselves lucky to be alive, or unlucky to have been injured? The empirical answer to this question is provided unequivocally in Teigen & Jensen: Not a single victim surveyed considered themselves unlucky. Downward counterfactuals occurred a magnitude of order more often that upward ones. And a follow-up after two years indicates that feeling lucky persisted for virtually everyone.

In summary, luck and chance are seen in the minds of some as distinct causal explanations. The studies just described generally explain the conditions under which luck concepts may be invoked, and establishes the importance of taking into account counterfactuals when studying luck perceptions. Counterfactual direction is unquestionably related to affective reactions to actual events, and this extends to judgements of luck. The many studies by Teigen form a veritable catalogue of these conditions. In the main, these contextual studies say little about the impact of lucky feelings on future decision making. They are retrospectively focused, drawing on either personal recall of past events or interpretation of the past of events of others. As such these studies may conflate lucky-gratitude and lucky-expectancy (see Section 1.6.1 for discussion of this distinction), though I hasten to add that the authors of these studies never claimed to measure expectancy type of lucky feelings. I note that the association of luck perceptions with gratitude is prominently demonstrated in one of the later studies by Teigen (1997), finding that in a social comparison context the phrase ‘I am lucky’ indicated gratitude.

2.2 Relevant Empirical Literature

I now turn to empirical literature which focuses on future decision making, using experimental manipulations which are outcome-based, but not narrative-based. These studies have a closer relation to the question: “Do lucky feelings influence decisions?” There are few published papers that inform my research question, and even fewer that are instructive to an experimental manipulation of lucky feelings. I discuss four papers in turn below. Each of these papers have a bearing on one or more elemental aspects of the broad research question: How to measure luck feelings; how to manipulate luck feelings; how luck belief is incorporated in study of luck feelings and risky choice; and what alternative explanations (namely, affect) are there for the influence of luck feelings on decision making.

2.2.1 Darke and Freedman (1997b)

An early set of three experiments reported in Darke & Freedman (1997b) was aimed at “exploring the effect of a lucky event and personal beliefs about luck on future behaviour” (p. 379). Although not specifically aimed at measuring lucky feelings, the manipulation check of the lucky event was an item asking the extent to which participants felt lucky at the time of the event. My interests focus on the influence of lucky feelings on risky choice as opposed to the effect of a lucky event, a subtle yet important difference. Lucky feelings are but one mechanism whereby a lucky event could influence risky choice, so the interests of Darke & Freedman (1997b) were broader than mine. The studies in Darke & Freedman (1997b) are nevertheless informative for the present work.

2.2.1.1 Description of the studies

The first experiment was a pilot. Due to some surprising results and a notable design concern, that first experiment was replicated in a more tightly controlled second experiment. The procedure was nearly the same across the two, apart from additional luck belief items in the second experiment and an alteration of the sequence in which they appeared. I describe that second experiment below, foregoing the first one because of its similarity and design concerns, adding only that findings from the first experiment were replicated quite closely in the second. Study participants (n=103) were Canadian first-year psychology students. The essential aspects to the study are:

- An experimental treatment of a lucky event;
- A measure of personal belief in luck;

- A performance task;
- A measure of performance confidence on the task; and
- A gamble on performance in the task.

The lucky event for all three studies in Darke & Freedman (1997b) was winning a lottery upon entry to the lab where the study was conducted. Winning the lottery entitled a participant to $5, which could then be used to gamble later. All participants in the lucky event condition won, although they were told that the chances of winning were only 10%. The lottery was of a slot-machine style with spinning numbers on a dial that had to match in order to win. The control condition did not experience the lottery, and were simply given $5 to gamble with. The measure of personal belief in luck was the first 10 items of the 12-item Belief in Good Luck Scale (Darke, 1993; Darke & Freedman, 1997a). (This scale is discussed at length in Chapter 3). Participants were either high or low Belief in Luck, using a median-split on the composite of the 10-items.

The performance task consisted of a visual perception exercise where participants guessed whether a 1 or 0 was more numerous among an array of 384 elements. There were a total of 20 sets, and the elements of the array didn't differ by more than 8. In other words there were only 8 more of one element than there were of the other, making this a very difficult task. Participants, on average, were correct in their guesses at the level of chance (51%). Instructions indicated that participants might have a "slight feeling" about their answers. Two dependent variables were measured: confidence, and a gamble on performance in the task.

Results from Study 2 are presented in Figures 2.1 and 2.2, which I've created from data they present. The authors interpret these results as follows: "People who believed in luck reacted to a lucky event by becoming more confident about their decisions and betting more money" (p. 383). I draw attention to the right-hand cluster of the two figures now, returning to the left-hand cluster momentarily. On average, participants in the Lucky-Event condition with a higher belief in luck demonstrate both higher confidence and gambles after they complete the performance task, relative to low belief in luck participants.

In the third and final experiment reported in Darke & Freedman (1997b), the authors used a different task for the dependent variable; one which was more familiar to

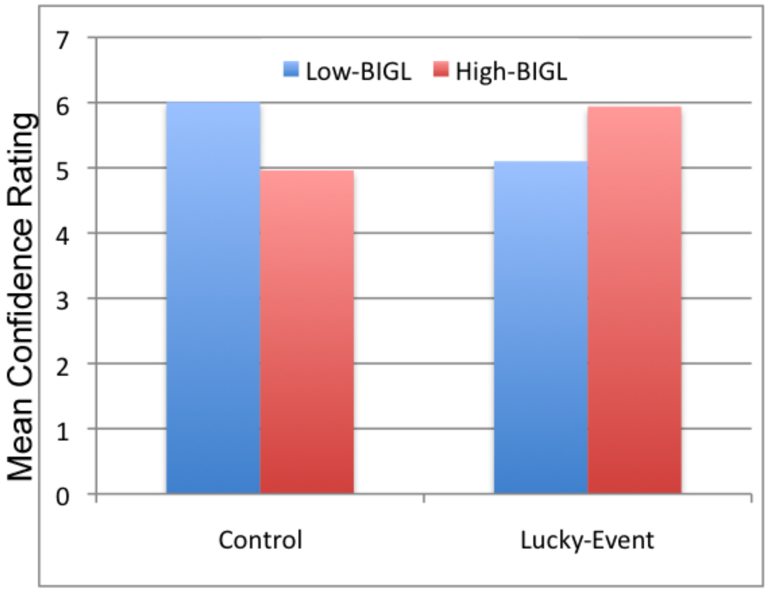

Figure 2.1: Mean Confidence Ratings, Study 2 of Darke and Freedman (1997b) - Higher ratings indicate greater confidence on a nine-point scale. Subjects were assigned to high and low luck-belief groups using a median-split.

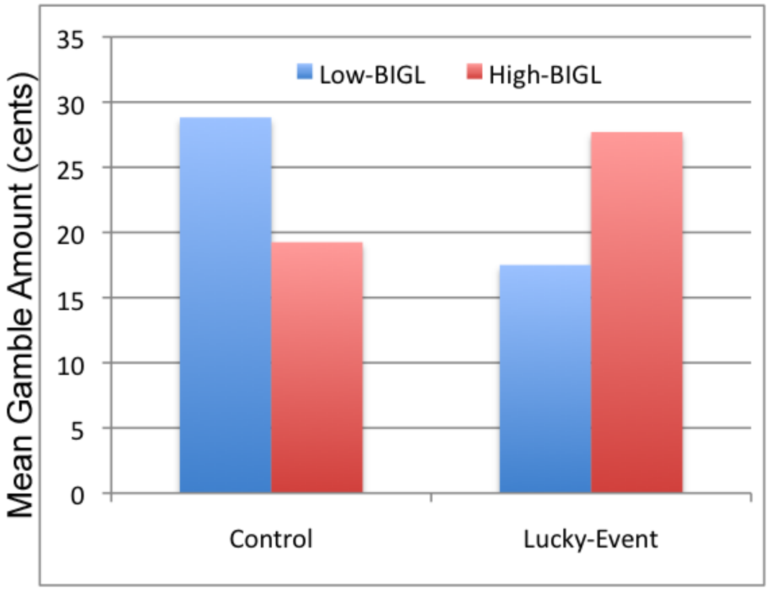

Figure 2.2: Mean Gamble (cents), Study 2 of Darke and Freedman (1997b) - Bets ranged from 1 to 50 cents. Subjects were assigned to high and low luck-belief groups using a median-split.

students. That task was an exam-style set of questions related to psychology. The behavioural dependent variables were questions guessed and questions answered incorrectly. For incorrect responses to questions, participants were penalised. Thus incorrect answers were interpreted as a greater level of guessing and therefore, of confidence. Skipping was interpreted as a lower level of guessing, and therefore confidence. The authors specifically expected that "those who do not believe in luck should skip more questions following a lucky event than control subjects" (p. 384).

Taking into account ability, as measured by results for a course final examination during a previous semester, Study 3 results followed a pattern that accorded with the first two experiments. That is, low ability participants who were high in belief in luck skipped fewer questions, relative to low ability participants who were low in belief in luck. Not surprisingly, the inverse pattern resulted for incorrect answers. That is, low ability participants who were high in belief in luck answered more questions incorrectly, relative to low ability participants who were low in belief in luck. There was little effect for participants who were high in ability.

The authors interpreted the results from Study 3 in the same manner as the first two experiments, positing that "Presumably, luck produced these effects through its influence on confidence... The experiments indicate that experiencing a lucky event can affect people's expectations about their subsequent performance on an unrelated task" (p. 386).

2.2.1.2 Discussion of Results

There are a couple of challenges to the interpretation of the authors. In the case of Study 2, the authors conduct a 3-way ANOVA that included the condition (lucky-event or control), the belief in luck (high or low), and the dependent variable (confidence or amount bet). The contribution of the control group to the overall F-statistic should not be overlooked. The authors draw attention to the effect of belief in luck for the control condition in terms of confidence ratings and amount gambled. Low belief in luck participants demonstrated higher confidence, betting and skipping, relative to high belief in luck participants. The left-hand clusters of Figures 2.1 and 2.2 clearly show that the control condition had almost the exact opposite effect as the lucky event condition. A similar pattern was seen in the results from Study 3. The authors offer two possible explanations, but discount both saying they are untenable, and then call for further research.

The literature on illusion of control (Langer, 1975), which Darke & Freedman reference in their paper, potentially provides some insight. Darke & Freedman note the similarity of their results to those expected from an illusion of control phenomenon, adding that there are some "distinct differences", notably that belief in luck was seen as a form of control over chance outcomes. That belief in luck gives rise to a sense of control is compelling. However, the authors note that "the phenomena are similar enough that they may be related, and further research should explore this possibility" (p. 387).

A second challenge, not so much to their interpretation of results as to my application of them in the present work, is that lucky feelings were not tested against any of the dependent variables. Recall that lucky feelings were measured in Study 2 using a 6-point scale, but used only as a manipulation check for the treatment and control group. Testing the relationship between (the continuous variable of) lucky feelings and (the also continuous variables of) confidence and amount gambled would have been interesting for my purposes. The manipulation check results are quite modest, albeit statistically significant. Participants in the lucky-event condition reported, on average, lucky feelings of 3.77. Those in the control group reported, on average, lucky feelings of 3.12. High belief in luck participants reported, on average, lucky feelings of 3.79. Low belief in luck participants reported, on average, lucky feelings of 3.12. Standard deviations were not provided. An interaction of condition and belief in luck was not statistically significant, something I would have expected if lucky feelings were a function of condition and belief in luck.

2.2.1.3 Implications

This early study by Darke & Freedman establishes a paradigm for testing lucky feelings against variance in risky choice, such as confidence and amounts gambled. This is the first empirical study to demonstrate a moderating effect of luck belief on relationship between a lucky event and risky choice (including confidence). However, there was no direct test of lucky feelings on decision making reported in their study, and the absence on an interaction effect between condition and belief in luck with respect to lucky feelings leaves some doubt regarding the specific effect of lucky feelings on decision making. This is not a criticism of Darke & Freedman (1997b), testing the effect of lucky feelings on risky choice was not the authors' objective. Rather, this is an opportunity to build on their work, examining one potential mechanism that might explain their results.

2.2.2 Wohl and Enzle (2002)

Three studies are reported in Wohl & Enzle (2002). The authors did not set out to test the influence of lucky feelings on risky choice. Rather, their focus was on the perceived deployment of personal luck as an instantiation of illusory control, in contrast to my objective. Nevertheless, some insights from their work are instructive for my research objectives.

2.2.2.1 Description of the studies

Their general hypothesis was that "people believe that they have a personal quality of luck that can be used to control logically uncontrollable games of chance" (p. 1390). The core of the theoretical contribution of this paper was to "expand the illusory control conceptualization. . . to include the possibility that. . . choice in games of chance inflates perceptions of personal luck" (p. 1390). The primary experimental manipulation in Study 1 was in the tradition of illusion of control experiments: either participants chose a lottery number (choice condition) or it was assigned to them (no-choice condition). A second and third study tested the idea that personal luck could be transferred via two laws of sympathetic magic, similarity and contagion. These studies are less informative to my purposes here, so I detail only the first one.

Prior to the first study, a pilot study demonstrated that participants from the student population preferred to choose, rather than be assigned a lottery number. In Study 1, the ultimate dependent variable was perceived chance of winning. Three dependent variables directly related to luck perceptions were measured (p. 1391):

1. whether '. . . luck is a quality of the person or a quality of the situation';
2. in relation to a lucky event, did a lucky thing happen to them or are they a lucky type of person?; and
3. the BIGL12 scale was used in a novel way to assess the 'transitory changes in luck understood as a personal quality.'

	Mean of Condition		
Dependent Variable	**Choice**	**No-Choice**	**F(1, 48)**
1) Luck is a Quality of a Person	3.92	2.11	5.01
2) I Am a Lucky Type of Person	4.04	1.92	21.97
3) BIGL12 Composite Score	45.13	34.96	16.49

Table 2.1: Results from Study 1 of Wohl & Enzle (2002) - Mean values of three dependent variables, by condition. All p-values $<.001$.

The BIGL12 composite score reflecting belief in luck was labile to the choice / no-choice manipulation in the pilot study, leading to the authors' adoption of the scale as a dependent variable.

2.2.2.2 Discussion of Results

Overall, the effects across all three studies were large. Table 2.1 reports the means for each condition in Study 1, along with F-statistics for the ANOVA tests. Dependent variable mean differences by condition were quite large, relative to the scales used. In Study 1, the chances of winning were estimated to be much higher, on average, by those in the choice condition as compared to the no-choice condition. The other three dependent variables I mentioned above were similarly affected by condition. Compared to the no-choice condition, participants in the choice condition, on average, reported higher responses to: 1) luck being more a quality of the person than the situation; 2) 'lucky' meaning they were a lucky type of person (as opposed to something lucky merely happening to them); and 3) higher composite score on the BIGL12 scale. Perceived chance of winning was correlated with BIGL12 composite score (0.64, $p < .001$) and with the other two variables (in the order as above, 0.47 and 0.50, $ps < .03$). The authors also conducted a test of mediation, demonstrating conclusively that the effect of experimental manipulation on perceived chance of winning was mediated by personal belief in luck. The authors conclude that "there is very strong evidence to support our general hypothesis that variations in self-perceived personal luck affect people's beliefs in their ability to control chance events" (p. 1392).

The three studies in Wohl & Enzle (2002) were thoughtfully designed, the results are consistent with a well explained phenomenon (illusion of control), and the effect sizes are strong. There is little or no concern with the technical aspects of the studies they report. One of the key outcomes of this study in relation to my own work is that it links the illusion of control phenomenon (Langer, 1975) with belief in luck, but uses belief in luck as a dependent variable. The use of the BIGL12 as a dependent variable was non-traditional, but doesn't appear to be problematic—the response of the BIGL12 composite to the manipulation is conclusive in that respect. Though non-traditional, recall that there is precedent for using luck beliefs as a dependent variable (Teigen et al., 1999).

Despite the strong findings, there remains some question as to whether the studies ruled out an alternative explanation to sympathetic magic, and this question is relevant to my work from a theoretical standpoint. According to the authors, belief in personal luck equates to, or influences, a belief in ability to *control* chance events. Following on from this *control-ability*, are effects on perceived chance of winning. However, belief in luck may not necessarily be only about belief in control as a mechanism. Belief in luck may lead to inflated expectations of positive self-relevant outcomes via enhanced ability in *prediction* of an event in advance, as in the case of a horse-race or coin toss. This belief in *prediction-ability* is an alternative mechanism that might explain the results seen in Study 1. The difference between belief in control and belief in prediction is that with control a person believes he or she can *influence* an outcome. With prediction, a person believes he or she can foretell an outcome. For participants who could choose, their prediction-ability could be deployed. Those who could not choose had no opportunity to exercise their prediction-ability. This might explain the differences in perceived chance of winning that was found in Wohl & Enzle (2002).

Perhaps I misconstrue the authors' use of the word 'control'. The authors may have intended control to subsume prediction. That is, prediction is a form of control. However, the paper is framed in the introduction from an illusion of control perspective, explaining that: "...the illusion of control may be understood as a pair of related errors made *during* some chance situations. First, people misperceive the chance event as being controllable. Second, people believe that they have and can use a conventional ability to *control the outcome* of the event" (p. 1388, my emphasis). The Langerian misattribution of control in chance events is usually thought of as a control of some element inherent to the process giving rise to the chance outcome, not merely a prediction of the outcome itself. Wagenaar & Keren (1988) found evidence, albeit anecdotal, to argue that luck is not deployed via a control mechanism, but rather it operates through prediction: “From our discussions with gamblers we learned that gamblers do not in fact believe that they can influence the roulette wheel. . . . Good luck may help one player to bet on the right number, while through bad luck other players bet on the wrong number. (p. 73)”

Whether by prediction or control, Wohl & Enzle (2002) found BIGL12 to be responsive to an experimental manipulation, rather than using it as a measure of a stable individual difference. That finding must be addressed in my work herein. I return to this issue later, in Section 2.2.3.2 below. The control versus prediction distinction is further explored in Chapter 3, where a measure of superstitious beliefs is used assist in the validation of a measure of luck beliefs. I turn now to a second paper by Wohl & Enzle, and integrate implications of the two momentarily.

2.2.3 Wohl and Enzle (2003)

Wohl & Enzle (2003) reports two studies that use a wheel of fortune paradigm to alter perceptions of personal luck, and then test for effects of personal luck on subsequent gambling behaviour. As in Wohl & Enzle (2002), perceptions of personal luck were measured by a composite BIGL12 score. The two experiments are almost identical in design and results, except that the second study had an extra independent variable (affect) and a control group. I will only describe and report results from the first, and briefly touch on the affect conditions of the second.

2.2.3.1 Description of the studies

Study 1 began with all participants receiving 5 gambling tokens, worth 20 cents each, and told they would be playing various games of chance as a study of individual differences in gambling knowledge. All participants then played a wheel of fortune game, experiencing the same outcome: they won an additional 10 tokens that could be used in a subsequent gambling task. The difference across conditions was that one half of participants nearly landed on bankrupt (near-loss condition), while the other half of participants nearly landed on jackpot (near-win condition). Thus, there was a counterfactual thinking element to the manipulation. Participants could readily imagine an alternative outcome to the one they actually experienced.

The participants then were offered the opportunity to gamble on a roulette wheel. The choices were restricted to red or black only. Responses to the BIGL12 were gathered before the roulette game was initiated. Participants were also asked to generate counterfactuals to the wheel of fortune game by listing "three ways in which the outcome of the wheel-of-fortune could have been different" (p. 186). Upon completion of the survey and before the roulette ball was spun, the experiment was terminated.

Compared to participants in the near-win condition, on average participants in the near-loss condition reported a higher BIGL12 (41.13 versus 33.87), and gambled more tokens (5.67 versus 3.93), ($ps < .02$). A mediation analysis indicated that BIGL12 mediated the relationship between the condition and gambling. Counterfactuals in the near-loss condition were on average downward (i.e., "I could have hit bankrupt"), whereas counterfactuals in the near-win condition were on average upward (i.e., "I could have hit jackpot"). An interesting challenge to Teigen (1995), counterfactual direction was not found to mediate condition and self-perceived luck, nor was it found to mediate condition and gambling.

The second study added an additional independent variable, that of affect. There was also a control condition where participants experienced no near outcome of an extreme degree, that is, neither bankrupt nor jackpot. The other affect conditions provided a balance between approaching the near-outcome or 'leaving' the near-outcome. That is, the wheel could stop either just before or just after either bankrupt or jackpot. As an associated dependent variable, the study also added the question: "I am currently feeling", with anchors from 'sad' to 'happy' on a 7-point scale.

Means by condition for the single item asking about current feeling were all about equal. The affect manipulation was also not associated with any other effects. The near-win and near-loss results were replicated, and by comparison to the control group, there was indication that participants in the near-win and control conditions were more similar in terms of dependent variable responses, relative to the near-loss condition.

2.2.3.2 Discussion of Results

As in Wohl & Enzle (2002), the BIGL12 was used as a dependent variable reflecting the "...transitory changes in the extremity of luck understood as a personal quality" (Wohl & Enzle, 2003, p. 186). Several years later, a publication by Maltby et al. (2008) offered some insights to using the BIGL12 as a dependent variable. Chapter 3 of this thesis goes into much greater detail regarding the measurement of luck beliefs using the BIGL12, but a short introduction to Maltby et al. (2008)'s work is warranted now.

Maltby et al. (2008) copied almost verbatim the 12 items from the BIGL12 and proposed an additional ten items to the BIGL12. They then investigated the dimensionality of the combined 22-item set, finding four dimensions to the belief in luck. The original BIGL12 items were found to belong to three different factors in the expanded 22 item set. One of those factors was *general belief in luck*, as reflected by the item, 'I believe in luck'. Four items from the original BIGL12 belonged to this factor. Another factor was *disbelief in luck*, reflected by the item, 'Being lucky is nothing more than random chance[1]'. Two items from the original BIGL12 were belonged to this factor. A third factor is *belief in being lucky*, reflected by the item, 'I often feel it's my lucky day'. Six items from the original BIGL12 belonged to this factor.

Using the BIGL12 composite score as a dependent variable could mask the precise factor or factors that might explain the changes arising from the manipulation in both Wohl & Enzle (2002) and Wohl & Enzle (2003). Using a composite of the BIGL12 does not provide a means to discern which factor (or factors) is responsive to the manipulations and which factor (or factors) is not. On closer consideration of the results, this could be important information. If participants' general belief in luck was responsive to the manipulation while other factors were not, then this is potentially another explanation for the effects found in Wohl & Enzle (2002) and Wohl & Enzle (2003). In other words, the responsive element of the measure used could have possibly been the general concept of luck rather than luck understood as a personal quality. This is an empirical question that would not have been obvious prior to Maltby et al. (2008).

The use of the BIGL12 as a dependent variable in Wohl & Enzle (2002) and Wohl & Enzle (2003) clearly demonstrated a response. However, I need a measure of lucky feelings. So, although Wohl & Enzle potential establishes a precedent for me to look to, the use of the BIGL12 as a dependent variable for my own work is somewhat problematic. The BIGL12 scale was originally intended as a "measure of individual differences in peoples beliefs about luck" (Darke & Freedman, 1997a, p. 489), not as a measure of lucky feelings. The BIGL12 may not reflect lucky feelings very well. It is possible, for example, that participants might experience a heightened sense of either general belief

[1]This item is reverse coded in the composite score for BIGL12 used in Wohl & Enzle (2002) and Wohl & Enzle (2003).

in luck or belief in being personally lucky (or both), and yet nevertheless not feel they are lucky at that moment in time. For example, it is not unreasonable that one might, upon experiencing a near-loss, think ‘I am usually a lucky person’, but not feel a sense of being lucky at that moment.

As mentioned above, the manipulation in these two studies relied heavily on counterfactual thinking. It is important to note that participants all experienced the exact same outcome. The only difference between conditions was the invoked reference to either a big near-win or a big near-loss. Reflecting the experimental manipulations, the counterfactuals in the near-loss condition averaged -.47, where a downward counterfactual (i.e., I almost lost it all) was coded as a -1, and an upward counterfactual (i.e., I almost won big) was coded as a 1. So not every participant in the near-loss condition was forming a downward counterfactual.

The measure of affect in Wohl & Enzle (2003) was a single item anchored by ‘sad’ and ‘happy’. This type of affect measure was later used in Jiang et al. (2009), detailed below. I will make further comments on the measurement of affect, but there is some question as to whether happiness equates to positive affect and whether unhappiness or sadness relates to negative affect.

2.2.3.3 Implications

Both Wohl & Enzle (2002) and Wohl & Enzle (2003) provide a good starting point for my own work. The use of the BIGL12 composite as a dependent variable invites a deliberate treatment of the scale in the design of my studies. I discuss luck belief measures in Chapter 3, where I develop and validate a reduced version of the BIGL22, the 16-item Belief in Good Luck Scale (BIGL16). That scale measures four different dimensions of luck beliefs. Prefacing that chapter, I take the view that luck beliefs are relatively stable, and the four dimensions must be taken into account in my studies. The dimensions of luck beliefs are nomologically associated with stable traits (i.e., cultural background), and also structurally differentiated in relation to each other and other validating constructs. The findings reported in Chapter 3 lead me to conclude that the appropriate sequence of items to measure luck beliefs places them prior to a manipulation.

My research questions pose luck beliefs as a moderator of environmental stimuli (i.e., prior outcomes of a game) and lucky feelings. This alone is sufficient to merit my application of luck beliefs in relation to the design of studies reported in Chapter 4 and 5. My usage however, in no way precludes luck beliefs being responsive to a manipulation. After all, the results of Wohl & Enzle (2002) and Wohl & Enzle (2003) are unquestionable. Further research on the priming of luck beliefs might clarify the priming role of gambling contexts on a particular luck belief dimension.

The imbalance of choice across conditions in Wohl & Enzle (2002) introduces another design possibility for my studies. I conclude though that incorporating an imbalance of choice in my designs would threaten the validity of any results I find. My objectives require that any effects are decoupled from explanations that arise from the illusion of control literature. In order to isolate the effects of lucky feelings on decision making, I will therefore hold choice constant, or allow it to randomly vary across conditions. Wohl & Enzle (2003) did not incorporate choice in their paradigm; instead they manipulated only implied counterfactual direction, but not closeness. The question of closeness raised in the works by Teigen remains unanswered. Findings from Wohl & Enzle (2003) with respect to average counterfactual direction were not particularly supportive of the role counterfactuals play in self-perceived luck. Most notably, counterfactual direction was not found to mediate condition and self-perceived luck, nor condition and amount gambled. Both counterfactual direction and counterfactual closeness will be incorporated into the designs of my studies.

Wohl & Enzle (2003) represents the first attempt to measure affect in a manipulation study of luck perceptions. I return to this topic in the discussion of Jiang et al. (2009) below, noting only that recommendations by affect researchers advocate more extensive measures of affect. Finally, neither Wohl & Enzle (2002) nor Wohl & Enzle (2003) report on measures of lucky feelings, which is of course understandable because this was not an objective in their studies. However, there is some indication that lucky feelings might be implicated with self-perceived luck. Again, a direct test of lucky feelings on decision making is paramount for my objectives.

2.2.4 Jiang, Cho, and Adaval (2009)

A recent paper by Jiang et al. (2009) sought to clarify the influence of lucky feelings in consumer behaviour. Citing the growing number of product promotions such as sweepstakes and the positive product evaluations they induce, Jiang et al. used priming tasks to elicit lucky feelings and a number of variables related to choice. Results of four studies conducted with Chinese students in Hong Kong indicate that lucky feelings are distinct from affect, and can influence choice behaviour.

2.2.4.1 Description of the studies

In Study 1 of Jiang et al. (2009) a backward-masked priming task resulted in group differences in self-perception of luck and affect. Two 'lucky' groups had a masked prime of either '8' or the Chinese character for 'lucky'. Two 'unlucky' groups had a masked prime of either a '4' or the character for 'unlucky'. (The numbers '8' and '4' are considered to be, respectively, lucky or unlucky for Chinese.) After a filler task, a single item, 'I often feel it's my lucky day', was used to measure self-perception of luck. And then a single item, 'how happy do you feel right now?' was used to measure affect. The lucky conditions corresponded to a higher mean self-perception of luck and affect, relative to the unlucky conditions. Perception of luck and affect correlated 0.21 ($p < .05$), and a covariance analysis showed these two dependent variables to be independent in their response to the experimental manipulation.

In Study 2, Jiang et al. used a subtle priming manipulation where a product to be evaluated by participants contained either an '8', a '4', or neither (in control conditions), in the price. Participants reported no conscious awareness of the priming, but nevertheless on average reported feeling luckier in the lucky condition as compared to the unlucky condition, as measured by an item asking to rate how lucky they felt "right now." The mean for the lucky group was 4.65, whereas the mean for the unlucky group was 3.13 (F [1,31] = 5.21, $p < .05$), on a scale of -5 to +5. Participants were offered the opportunity to submit an entry form to a lottery awarding gift certifications. On average, lucky-condition participants reported a greater likelihood of winning as compared to unlucky-condition participants. A mediation analysis indicated ($p = .08$) that their measure of lucky feelings mediated the relationship between the experimental manipulation and expectation of winning the lottery.

Study 3 began with participants judging the attractiveness of 20 numbers. The majority of targets in the good luck condition contained the number '8' and the remaining numbers were neutral. The majority of targets in the bad luck condition contained the number '4' in and the remaining numbers were neutral. Participants then evaluated a product (a bag of potato chips) under both a lottery and a discount promotion. Under the lottery promotion, the product was evaluated where would-be purchasers were entered into a draw for a movie ticket. Under the discount promotion, the product was evaluated on 'liking' where the price of the product was reduced by about the (as pretested) perceived difference in the subjective utility of the draw for the movie ticket. There was no difference in the good luck and bad luck manipulations for ratings of the product promoted using a discount. There was however a significant difference by treatment group in the ratings of the product promoted using a lottery. The good luck group rated the lottery-promoted product on average more favourably (2.04) than the bad luck group (1.04), and this difference was statistically significant (F (1, 104) = 7.02, $p < .01$). Participants then responded to a lucky feelings item asking how lucky they felt "right now." Participants in the lucky condition reported on average higher lucky feelings than those in the unlucky condition: 5.79 versus 4.72 (F [1, 104] = 7.80, $p < .01$). As in Study 2, a mediation analysis indicated ($p < .05$) that their measure of lucky feelings mediated the relationship between the experimental manipulation and the dependent variable, evaluations of the lottery-promoted product.

Study 4 in Jiang et al. (2009) did not measure lucky feelings. Study 4 employed the same manipulation as Study 3, and examined effects of the manipulation on lottery participation and investment choice of an amount hypothetically inherited. Other measured variables were regulatory focus (Higgins, 1998), affect (as measured by a single item asking about happiness), and the BIGL12. The sequence of the study placed the regulatory focus first, the dependent variables of lottery participation and investment choice second, then the affect item and the BIGL12. Although interesting in its own right, this study is not as relevant for my interests as the previous three because it excluded a measure of lucky feelings.

2.2.4.2 Discussion of Results

The manipulations employed by Jiang et al. (2009) were interesting and demonstrated effects on dependent variables. The manipulation in the Study 2 (inclusion of lucky or unlucky numbers in the product price) reflected a naturalistic intervention that could readily be applied to practice with Chinese consumers. There were indications that lucky feelings mediated the manipulation and an expectation of winning a lottery. The studies used three different priming manipulations, and the different types of priming employed represent a well-rounded exploration of different priming techniques. The conclusion can be made from these studies that priming can invoke behaviour and feelings that are associated with luck. The studies by Jiang et al. (2009) should be instructive to both scholars and practitioners of consumer psychology.

Jiang et al. (2009, p. 182) suggest that their studies may be culture-bound to some extent. There is evidence to suggest that Asian-background individuals hold stronger luck beliefs (Church, 1987; Darke & Freedman, 1997a; Weisz, Rothbaum & Blackburn, 1984). However, if luck beliefs are merely stronger for Asians, compared to Westerners, then the important element that would systematically differ from a non-Asian sample would be strength of belief and not the nature of the belief. A replication using the particular luck references of 4 and 8 in a Western sample is not likely to yield the same results given their cultural specificity, though the word primes of 'lucky' and 'unlucky' could reasonably be expected to do so.

There is a possible inconsistency between findings of Study 1 and Study 4 of Jiang et al.. In Study 1, the measure for lucky feelings had the same wording as an item from the BIGL12 scale (i.e., "I often feel it's my lucky day"). This single item was responsive to the masked prime manipulation in Study 1, but the BIGL12 composite was not responsive to the lucky/unlucky manipulation in Study 4. The finding that the BIGL12 composite was not responsive to the manipulation in Study 4 is also inconsistent with a finding from Wohl & Enzle (2003), which found a response using the same composite, albeit for a different manipulation (near-loss or near-win on a wheel of fortune). It may be then, that the fourth study of Jiang et al. was a failure to replicate the findings from Wohl & Enzle (2003), or that the single-item was particularly responsive to a priming manipulation.

Studies 2 and 3 of Jiang et al. (2009) found that a direct measure of lucky feelings (i.e., "How lucky do you feel right now?") mediated two different priming manipulations and the likelihood of winning a lottery, as well as the liking of a product promoted using a lottery. Study 4 employed the same manipulation as Study 3, and so integrates the two studies across different dependent variables. However, Study 4 did not report a measure of lucky feelings. So, although lucky feelings were demonstrated to mediate number primes and the product-evaluation dependent variables in Study 2 and 3, it cannot be concluded definitively that lucky feelings also mediate a number prime and risky choice in Study 4.

In summary, studies reported in Jiang et al. (2009) are well designed for the authors' objectives, which related to consumer psychology. The findings are robust and interesting, providing good coverage of different types of subtle manipulations that relate to luck.

2.2.4.3 Implications

Despite the quality of the studies reported in Jiang et al. (2009), there were some limitations in the applicability of their findings to my own work. Namely, the sample differed in a potentially important way from the sample population convenient to me. The measurement of lucky feelings was inconsistent across the studies, but this did not threaten the results. However, the absence of a measure of lucky feelings in Study 4 limits conclusions that can be drawn regarding the mediating role of lucky feelings for the effect of a luck manipulation on risky choice.

The ultimate dependent variables used in Jiang et al. differ in important ways from the risky choice measures I'm interested in. Evaluation (i.e., liking) of a product, in this case a bag of chips, may not equate to a gamble or investment given the underlying immediate utility of the product in question. (Recall that the two products were priced at a level that equated the underlying utilities of the discount and the expected value of the lottery prize.) Although there remains some question as to the mediating role of lucky feelings to risky choice, this is a finding to suggest the influence of lucky feelings on risky choice.

The measure of lucky feelings used in Study 2 and 3 appears to be a good measure for lucky feelings. The possibility of using the BIGL12 as a measure of lucky feelings was addressed in my discussion of Wohl & Enzle (2003), and the conclusion there is bolstered by these possible inconsistencies. Measuring lucky feelings using a direct question ("How lucky do you feel right now?") seems the best choice given the various results described above and my objectives. It most closely measures the type of lucky feeling I describe in Chapter 1. Although this item does not distinguish between lucky-gratitude and lucky-expectancy, the context in which the statement is rated can infer the meaning to some extent. If the item is presented following a narrow escape from extremely negative consequences, it is likely to reflect gratitude. If the item is presented with the salient question of a gamble or investment looming, it is likely to reflect expectancy. In practical terms though, the question of which measure to use, the PGL item or a direct question, is mooted by my interest in modelling luck beliefs as a moderator of prior outcomes and lucky feelings. Using the same item as a moderator and dependent variable would be both inappropriate and uninteresting. Whether 'luck understood as a personal quality' (as measured by the BIGL12 composite, or alternatively using a single item from that scale) equates to lucky feelings is perhaps a fine-grained distinction for others, but the inclusion of luck beliefs as a moderator is tightly integrated with my choice of measure for lucky feelings. It would obviously be inappropriate to model PGL, to which the item 'I often feel it's my lucky day' belongs, as a moderator of a manipulation and the same item.

As in other studies discussed previously, the item used to measure positive affect, was a question about happiness. Green, Goldman & Salovey (1993, p. 1037) note that positive affect as defined by Watson, Clark & Tellegen (1988) "...comprises moods such as excited or enthusiastic rather than happy; negative affect refers to moods such as distressed or nervous rather than sad." Tellegen, Watson & Clark (1999, p. 297) claims that "Happiness and sadness form a largely unidimensional bipolar structure, but PA [positive affect] and NA [negative affect] are relatively independent." So there is some question about the use of happiness and sadness items to measure affect. A more extensive measure of affect is required for my purposes, and this conclusion is affirmed in the review of Jiang et al. (2009). Rather than using a single item to measure happiness, I will use items from the Positive and Negative Affect Scale (Thompson, 2007; Watson et al., 1988, PANAS).

Another prominent issue raised by the design of Jiang et al. (2009) regards the use of a priming manipulation. The priming manipulations in Jiang et al. (2009) represent a potential approach I could use, if the manipulation did in fact influence lucky feelings, as measured by an item that asked about lucky feelings directly. It is possible thought that a subtle priming manipulation of lucky feelings is weaker than a more explicitly luck-related one, such as that found in Wohl & Enzle. Moreover, there is a question as to whether the priming manipulation used in Jiang et al. (2009) might be culture-bound. The sample population I had most convenient access to consisted of undergraduate psychology students in a major metropolitan city in Australia. It was therefore important to determine the efficacy of manipulations similar to Jiang et al. (2009) for potential participants from that population. Presumably, my sample population was more similar to those in the studies by Wohl & Enzle, so I am less doubtful of the efficacy of that type of game-based manipulation.

I conducted a replication study Jiang et al. (2009) using a large sample (n=667) and concluded that their masked prime manipulation in Study 1 is not appropriate for my objective of measuring the influence of lucky feelings on decision making. I used backward masked priming of the words 'lucky' and 'unlucky' using the same method they report. Participants were then asked a question about lucky feelings, "How lucky do you feel right now?" The ultimate dependent variable I measured was participant evaluations of either a lottery-promoted product or a discount-promoted product. There was no statistically significant difference between priming-group means for a direct measure of lucky feelings (i.e., "How lucky do you feel right now?") as determined by one-way ANOVA (F (1,666) = .882, $p = .348$). There was however, an effect for the priming condition, but for both product evaluations, which is a failure to replicate the pattern reported in Jiang et al. (2009). For them, a lottery-promoted product responded to the priming condition in a different manner to a discount-promoted product. This failure to replicate the findings may be due to culture differences between the Hong Kong Chinese and Australians. The failure to replicate an effect on lucky feelings could also be due to a difference in the lucky feelings measure. Of course, there may be alternative explanations for the absence of findings. But as a test of the combination of a subtle priming manipulation and a direct measure of lucky feelings, the null finding from this pilot indicates a different approach should be taken for my objectives.

Notwithstanding the limitations of Jiang et al. (2009) in relation to my work herein, their studies demarcate the boundary of current understanding regarding the influence of lucky feelings on decision making. Taken together Jiang et al. (2009), Wohl & Enzle (2002), Wohl & Enzle (2003), and Darke & Freedman (1997a) provide a solid foundation for exploring lucky feelings, luck beliefs, and decision making. In the section to follow, I conclude this chapter with a discussion of the issues raised in the literature review, and introduce research questions I'll address throughout the remainder of the work.

2.3 Summary of Research Issues

In this final section, I summarise the issues that arise from the introduction and literature review, and introduce the research questions that will be addressed through the remainder of the present work.

2.3.1 Luck Beliefs

The first and most fundamental issue that emerged from the literature regards the measurement and dimensionality of belief in luck. Logically, it seems reasonable to expect that a belief in luck is required in order for a person to experience lucky feelings. It is important to establish the measurement of belief in luck with some confidence in order to explore the wider context of lucky feelings and decision making.

There are conflicting views on the measurement of belief in luck. Darke & Freedman (1997a) found only one dimension in the 12-item BIGL, but Maltby et al. (2008) found four in an expanded 22-item scale. Wohl & Enzle (2002) and Wohl & Enzle (2003) use the earlier scale as a dependent variable. Jiang et al. (2009) use a single item from the same scale as a measure of lucky feelings.

Several questions surface when attempting to integrate this past empirical work. How many dimensions are there to a belief in luck? What are they? Are all of them required to understand their influence on lucky feelings and decision making? Are all 22 items required, or is there a more economical way of measuring luck beliefs? Where does each dimension of luck belief belong in a larger model of decision making?

In order to understand the role of luck beliefs in decision making it is important to understand the dimensionality of luck beliefs and to have a reliable and valid measure of luck beliefs.

In Chapter 3, I refine and validate a 16-item measure of beliefs in luck, the BIGL16. The items in the BIGL16 correspond to four different dimensions of the belief in luck. The four different dimensions are differentially predictive of various dependent variables, as the reader will soon see. Unsurprisingly, a belief in luck moderates predictors of lucky feelings.

2.3.2 Counterfactual Thinking

A second issue that emerges from the literature regards counterfactual thinking as a core element of luck attribution and lucky feelings. Teigen (1995) and Teigen (1996) assert that counterfactuals are important in judgements of luck. However, Teigen's work almost exclusively relies on vignettes and judgements of feelings of fictitious characters in a story. He makes a compelling argument that counterfactual direction is an important component of luck attribution, based Norm Theory (Kahneman & Miller, 1986).

However, Wohl & Enzle (2003) did not find that counterfactual direction was a mediator of their experimental manipulation and self-perceived luck (i.e., the single item from the BIGL12 scale). Counterfactual direction also did not mediate the manipulation and gambling behaviour. This lack of empirical support for counterfactual direction is surprising. This is even more so given that counterfactual direction subsumes counterfactual closeness, and counterfactual *closeness* is shown in Teigen (1996) to covary with participants' lucky-feelings judgements of vignette characters. The vignette-based studies by Teigen suggest that a manipulation of counterfactual closeness for participants *personally* should result in lucky feelings. It is possible though, that the judgements of counterfactual direction or closeness of fictional characters' may not be representative of the actual personal experience of counterfactual closeness. Rating of lucky feelings likely to be experienced by fictional characters may differ from the lucky feelings people personally experience in reaction to an actual outcome with a counterfactually close alternative. Alternatively, the judgements of lucky feelings in relation to vignette characters may reflect retrospective type lucky feelings (lucky-gratitude) and not prospective type lucky feelings (lucky-expectancy). Given these mixed results, Teigen's assertions that counterfactual direction and counterfactual closeness are at the core of luck attributions and lucky feelings require further investigation.

There are both conceptual and practical questions in relation to this investigation regarding the operationalisation and measurement of counterfactual closeness. How should counterfactual closeness be operationalised and measured? How do counterfactual closeness and direction compare in terms of prediction of lucky feelings? Does counterfactual closeness have more influence for those experiencing negative outcomes, relative to positive outcomes? Is there a difference in the effect counterfactual closeness has on lucky feelings between a recalled personal experience (retrospective) and an immediately experienced outcome (with a prospective target decision)? These questions are explored in depth in Chapters 4 and 5.

2.3.3 Affect

A third issue that emerges from the literature regards the role of affect in luck attributions, lucky feelings, and the influence of lucky feelings on decision making. There are no luck studies I'm aware of that have used a measure of affect that has been subjected to validation, although there are two studies that use a proxy of questionable validity.

In Study 2 of Wohl & Enzle (2003) participants' provided a rating of their feelings on a single item for which the scale ranged from 'sad' to 'happy'. Jiang et al. (2009) also asked a question about participant happiness. Wohl & Enzle (2003) found no effect of their manipulation on the feeling item. Jiang et al. (2009) however, found that happiness was higher in the lucky condition and lower in the unlucky condition. Happiness and lucky feelings correlated moderately. Thus, these two studies are in disagreement regarding the relationship of affect to lucky feelings. Even if they were in agreement, the 'happiness' measures do not conform to recommendations regarding measurement of affect, as explained above. So, there is some question as to whether or not basic questions regarding affect and lucky feelings have been definitively answered. There are several possible ways that affect and lucky feelings could be related with respect to a third, dependent variable. Are 'lucky feelings' synonymous with affect? Or perhaps affect predicts lucky feelings and risky choice, but lucky feelings have no effect on risky choice? Do lucky feelings mediate the effects of affect on risky choice, either partially or fully? Do lucky feelings have any effects on risky choice independent of affect. Or, is it the case that lucky feelings and affect predict different kinds of risky choice?

Affect, and its relation to lucky feelings is explored in depth in Chapter 4. A validated measure of affect is used in the study reported therein, and tested as a predictor of lucky feelings in the context of counterfactual thinking.

2.3.4 Lucky Feelings

A fourth issue emerging from the literature regards the measurement of lucky feelings, and the direct testing of the impact of lucky feelings on decision making. It is important to test the impact of lucky feeling on decision making because lucky feeling is the most likely mediator of the relationship previously found between luck beliefs and choice. As I explained in the previous chapter, a prospective-type luck feeling potentially provides the luck-believing decision maker with information that might alter calibration of outcome probabilities. Darke & Freedman (1997b) only use lucky feelings as a manipulation check of the experimental manipulation in their second study, asking simply if participants felt lucky at the conclusion of the slot-machine lottery, before eliciting a gamble amount. The effect of the manipulation on lucky feelings was small. They do not report how lucky feelings related to decision making.

As mentioned before, Wohl & Enzle (2002) and Wohl & Enzle (2003) use items from the BIGL12 as a measure of the "personal deployment of luck". The concept here is something akin to lucky feelings, but not precisely lucky feelings. The *measure* on the other hand is that of a belief, and the very essence of a belief is that it is stable and enduring. Inarguably, there are strong experimental manipulation effects with respect to personal deployment of luck, as measured by items from the BIGL12. However, it is unlikely that a personal belief of any kind is so strongly moved in an experiment. More likely is that lucky feelings affect the salience of luck beliefs, temporarily heightening responses on a belief scale.

Jiang et al. (2009) use a direct measure of lucky feelings, "How lucky do you feel right now?" This measure seems appropriate for my purposes herein, and will be used in Chapter 5 in service of the core question of the research presented herein: Do lucky feelings influence decision making? An alternative measure of lucky feelings, more closely related to the luck dimensions described by Wagenaar & Keren (1988) is used in Chapter 4.

Further questions are immediately triggered: If lucky feelings influence decision making, how? There are competing hypotheses regarding the direction of that influence. Will lucky feelings results in increases in risk-taking, or decreases (as would be consistent with the 'mood maintenance hypothesis')? How, or how strongly, do lucky feelings relate to unlucky feelings? Do lucky and unlucky feelings have the same antecedents? Do those experiencing positive prior outcomes experience a reduction in unlucky feelings, an increase in lucky feelings or both? What about those experiencing negative prior outcomes?

In Chapter 4, I measure lucky feelings, modelling them in the context of affect, counterfactual thinking and overconfidence. I extend findings in relation to lucky feelings in Chapter 5, where I incorporate unlucky feelings in a study of reactions to a competitive game outcome.

2.3.5 Dependent Variables and Experimental Manipulations

A fifth issue that emerges from the literature is that of the choice of dependent variables. Darke & Freedman (1997b) tested the effect of their lottery-winning manipulation on confidence and a gamble. Wohl & Enzle (2002) used perceived chance of winning as a dependent variable of a choice versus no-choice manipulation. Wohl & Enzle (2003) investigated the effects of a near-win versus near-loss manipulation on subsequent gambling behaviour. Jiang et al. (2009) measured product evaluations as a dependent variable of priming manipulations. Of these dependent variables, those in Jiang et al. (2009) are least interesting for my purposes. The others are directly relevant for my interest. But which of these will be most responsive to lucky feelings? Which will be the least? I will use a mixture of these questions, examining confidence, gambles and a number of other non-gambling questions regarding risky choice.

A sixth issue that emerges from the literature is that of experimental manipulations. There is of course, no single best way to manipulate lucky feelings. The constraints and objectives of the research must be brought to bear on the selection of an experimental manipulation. My objectives in this research included the design of a manipulation that did not require payment of money to subjects, and did not rely too heavily on a gambling theme. Much of the research by Wohl & Enzle has a focus on gambling and integrates with their broader work related to profiling problem gambling antecedents and consequents as well as treatment readiness. My interest is in the effects of lucky feelings on decisions involving risk without focusing on an explicit gambling theme, which is more in line with Darke & Freedman (1997b).

Is there an effective experimental manipulation of lucky feelings, that will yield a more intricate understanding of the role of lucky feelings and luck beliefs in decision making? What of the distinction between Teigen, and Wagenaar and Keren's retrospective approach, and the more future oriented game-style approach of Wohl and Enzle? I report on studies using two manipulations that result in changes in lucky feelings as well as ultimate depending variables including overconfidence and risky choice. In Chapter 4, participants recall a past event and formulate counterfactuals. Resulting lucky feelings are tested against two different kinds of overconfidence. In Chapter 5, participants compete in a game of chance that elicits lucky feelings. These lucky feelings are tested across different risky choice measures, in separate analyses for winners and losers.

2.3.6 A Holistic View of Lucky Feelings and Decision Making

Most of the issues discussed thus far—luck beliefs, counterfactual thinking, affect, and dependent variables—are not only important independently, but also have interdependencies with one another. The work in the area of luck to date has relied on traditional approaches to design and statistical analysis that include ANOVA, correlation, and multivariate regression. These statistical approaches limit the extent to which the system of variables can be holistically represented and tested. The complexity of the domain of enquiry, entailing many different variables, interactions of variables, and mediating paths of variables, calls for a structural modelling approach. As a final issue emerging from the literature discussed above, the existing work is constrained in respect of the possibilities that a modelling approach affords.

Mediation analyses are conducted in Wohl & Enzle (2002), Wohl & Enzle (2003), and Jiang et al. (2009). However, these are limited to testing the mediating effect of items from the 12-item belief in good luck scale in the relationship between experimental condition and perceived chance of winning and amount gambled. The belief in luck scale has multiple dimensions, and the role of belief is better conceptualised as a moderator than a mediator. Furthermore, my interest is in testing lucky feelings as a mediator of multiple influences and multiple dependent variables. This results in a rather complex nomological net, especially when counterfactual direction or closeness is taken into account.

Throughout these chapters I use both conventional statistical analyses and a more sophisticated modelling technique, Partial Least Squares Path Modelling (PLS), to build a system-level view of the many variables implicated in luck beliefs, lucky feelings and risky choice. For the reader unfamiliar with PLS, I provide a primer for the modelling technique in the Appendix.

2.4 Overview of Empirical Chapters

The three chapters that follow attempt to integrate these six research issues that have been identified from the literature. Chapter 3 primarily addresses the measurement of luck beliefs. The findings from Chapter 3 carry forward to Chapters 4 and 5, namely in the specification of the validated five-item constructs of PGL and PBL.

Chapters 4 and 5 have in common that they both report a test of the impact of luck feelings on a measure. However, they differ in that the study reported in Chapter 5 is restricted to a prospective-type of luck feeling, whereas the study reported in Chapter 4 is less precise. As is often the case in a long programme of research, advances in understanding over time can result in slight (and not-so-slight) changes to the measures, experimental manipulations, and a host of other factors. Thus was the case with this research programme reported herein.

Chapter 3

Validation of the 16-item Belief in Good Luck Scale (BIGL16)

3.1 Introduction

This chapter describes the development and validation of the 16-item Belief in Good Luck Scale (BIGL16). The BIGL16 contains items that measure four luck belief dimensions: A general belief in luck, a belief that one is personally lucky, a belief that one is personally unlucky, and finally a belief regarding the relationship of luck to random chance.

As I discuss in later chapters, certain dimensions of luck beliefs are likely to act as an important moderator of the relationship between manipulations of prior outcomes (i.e., winning in a game of chance) and lucky feelings. Luck beliefs may also moderate the relationship between lucky feelings and decision making. Thus, reliable measures of validated luck beliefs dimensions are necessary in the exploration of the thesis that lucky feelings influence risky choice. How to model luck beliefs in later chapters, where I test the effects of manipulations of lucky feelings, is a question partly regarding factor structure. The question of how to model luck beliefs can be thought of at two levels: 1) the *items* that measure a given dimension of belief in luck; and 2) the relation of a given *dimension* of belief in luck to other dimensions of belief in luck as well as other related concepts.

The *items* that measure a given dimension of belief in luck can be examined in terms of both convergent and discriminant validity. With respect to convergent validity, one seeks to assess whether a set of items measures the dimension they purport to measure. With respect to divergent validity, one seeks to assess that a particular item is restricted in its response to other latent dimensions of luck beliefs. Unidimensionality is the first of several requirements for acceptable levels of convergent and discriminant validity. The relation of a given luck belief *dimension* to other luck belief dimensions and to other related concepts, such as superstitious beliefs, is a question of nomological validity. Demonstrated nomological validity of luck belief dimensions lends increased confidence to models I propose and test in subsequent chapters.

I employ traditional factor analytic techniques in this chapter, but these are only the starting point for a more sophisticated analysis based on partial least squares (PLS) modelling[1]. A PLS modelling approach is especially useful in this investigation because, relative to more traditional types of analysis, items can be more efficiently examined in terms of both convergent and discriminant validity. Additionally, the oft-overlooked criterion of nomological validity is examined with greater ease using PLS modelling. In this chapter, I examine nomological validity by embedding luck belief latent constructs in models that also include superstitious beliefs, cultural background, verbal reasoning ability, and understanding of randomness.

The chapter begins with a brief introduction, then proceeds in two major parts. The introduction opens with a history of luck beliefs and luck belief measurement. I then detail the items that were considered for inclusion in the BIGL16. I conclude the introduction by laying out topics in the two major parts of the chapter. Part one of the chapter examines the 12-items from the Belief in Good Luck Scale (Darke & Freedman, 1997a, BIGL12). Part two examines the 22-items from the Darke and Freedman Beliefs Around Luck Scale[2] (Maltby et al., 2008, BIGL22).

[1]For the reader unfamiliar with PLS, the Appendix contains a primer on PLS modelling. The primer offers a general introduction to the technique, as well as information relevant to the interpretation of PLS results presented throughout the thesis. The basic output of PLS is equivalent to those of regression: β values; R^2 values; and t-values which correspond to a p-value for a given sample size (i.e., degrees of freedom). There are however, several advantages to using PLS over regression, which are detailed in the primer.

[2]The names of these scales are understandably confusing, given that Maltby et al. (2008)'s 22-item scale carries the names of Darke & Freedman, the authors of the 12-item scale. I provide historical context to clarify in the following passages.

3.1.1 The History of Luck Belief and Luck Belief Measurement

In an ancient context, luck, fortune, destiny, and deity were intimately intertwined. Magico-religious symbols and rituals were the manifestation of beliefs that health, prosperity, power and even eternal life could be had by appeasing a supernatural being or force. Returning to Cohen (1960, p. 122):

> The primitive belief, shared by mythologies of antiquity, that man's fortune, for good or ill, is carefully controlled, produced a range of luck-bearing devices to ensure some participation in this control. Many of these devices, such as amulets and talismans, still enjoy a wide currency. The amulet was supposed to provide its wearer with continuous protection against evil, whilst the talisman could bring good fortune as well as guard against some specific object or disease.

One such amulet, the likeness of the scarab beetle, is worth mentioning because it embodies so well the melding of luck and fortune across a number of isolated ancient cultures. The first documented human use of the scarab beetle for magico-religious symbolism was 2,700 BCE (Crowson, 1981). The scarab beetle was revered among ancient Egyptians due to certain likenesses it shared with both the sun god, Ra and the creator god, Kheper. As such, amulets and other figures of scarab beetles were crafted by hand and inscribed with text on the flat, underside of the beetle figure (See Figure 3.1). Inscriptions varied, and included the commemoration of special occasions such as a marriage, successful hunt, or victorious battle. Other inscriptions were more simple, with only the name of the wearer or an incantation to bring health, love, luck and the like. For their own idiosyncratic reasons, ancient peoples from all around the Mediterranean, Northern Europe, North America, and Australia incorporated Scarabaeoid symbolism into magico-religious behaviours (Ratcliffe, 2006). Other insects, including the cricket, dragonfly, lady bug, butterfly, preying mantis and bee also enjoyed a mystical status among various peoples of the world. Many of these insects are still associated with good luck or mystical elements.

Entomophagy, the consumption of insects by humans, was practiced by many ancient peoples (and continues to be a part of the diet of some in the modern-day). For some, entomophagy was merely nutritive. Others though, consumed insects in a ritual fashion as a means of treatment for illness, or even as 'imitative magic': acquiring a characteristic of an insect through ingestion. For example, the Hottentots of southern Africa consumed the conspicuous horn of the rhinoceros beetle as an aphrodisiac (Klausnitzer, 1981). Insects generally, and beetles in particular, have not always been revered though. In an ironic fall from grace among Europeans, beetles were excommunicated from Catholic Church in late 15th century because of the damage they caused to crops (Ratcliffe, 2006).

Magico-religious beliefs may date to the dawn of *homo sapiens*, as suggested by archaeological discoveries of Löwenmensch, or 'lion-men' (see Figure 3.1), thought to be produced by the Aurignacian people who lived more than 30,000 years ago in modern-day Germany. The Löwenmensch were carved from mammoth tusks and had the body of a man and the head of a lion. This melding of human and animal is interpreted as an indication of the practice of shamanism by some archaeologists (Conard, 2003; Lewis-Willaims, 2002). The discovery of multiple carvings in different locations indicates this practice may have been a widespread.

Figure 3.1: Magico-Religious Artefacts: Scarab and Löwenmensch - To the left is pictured a steatite-engraved scarab underside commissioned by Pharaoh Amenophis III in approximately 1,400 BCE to commemorate his queen, Tiye (Creative Commons). To the right is pictured a mammoth-tusk carving of a 'lion-man', found in present-day Germany and carbon-dated to approximately 30,000 BCE (Creative Commons).

Most certainly the belief in luck in modern Western society is radically different from the convictions of ancient peoples that the world was controlled by a magical force. However, some features are common: the development of a system of beliefs and associated practices that yielded prediction and explanation. At some point in time—perhaps during the Enlightenment—the idea of luck became differentiated from that of deity, at least for Westerners. Regardless of when or to what extent luck and deity were differentiated, the symbols and practices related to luck continue to bear resemblance to religious symbols and practices: a 'lucky' rabbit's foot might compare to a Christian cross worn around the neck; as might also compare the crossing fingers and genuflecting.

The relation of luck beliefs and magico-religious beliefs through the ages must surely be a fascinating history, but it is not the topic of this chapter. This chapter is devoted to the empirical measurement of luck belief. These ancient magico-religious artefacts of luck belief provide an *indication* that something akin to luck belief existed long ago. In a similar way, the first measures of luck belief were *indications* of luck belief. Attribution to luck versus skill (Rotter, 1966; Weiner, 1974) was perhaps an accidental measurement of luck belief. As mentioned before, luck and chance were conflated in those early attribution theory measures: the focus of that research was on discerning reward as contingent on one's own behaviour versus independent from it. The first instance of a measure of attribution to luck delineated from both skill and chance is found in Keren & Wagenaar (1985), the sample for which was professional Blackjack players:

> In playing Blackjack there are three important factors, namely chance, skill, and luck. How important is each of these three factors? Give your answer in percentages so that they add up to 100%.

The endorsement of luck as a factor in the game of Blackjack assumes a luck belief. However, such an endorsement only indicates a luck belief, it does not measure it. Could we say that a person who viewed luck as being 50% important in Blackjack (or some other task for that matter) had a stronger luck belief than someone who viewed luck as being 10% important? Perhaps the difference in ratings is due to differences in game perceptions and not luck beliefs.

After Keren & Wagenaar (1985), the first psychometric instrument designed to specifically measure belief in luck was formulated in the 1993 doctoral thesis by Darke, and later published in a peer-reviewed journal (Darke & Freedman, 1997a). This 12-item scale later appeared in further work by Darke, in what appears to be a one-off investigation of confidence and risk taking in groups, with belief in luck being a predictor (Darke & Freedman, 1997b). A French-language belief in luck scale was proposed some years later (André, 2006). There also have been scales related to luck belief that have been developed for use in research focusing on gambling themes. One example of these is Wohl, Stewart & Young (2011). In the Wohl et al. scale, seven out of twelve items specifically mention gambling. Examples of such items are, “My wins are evidence that I have luck related to gambling.”; and “My luck plays an important part in my gambling.”

As I use an English-speaking population, the André scale cannot be used. Furthermore, my focus on risky choice, and avoidance of overtly gambling-themed paradigms implies the Wohl et al (2011) scale may be inappropriate for my uses. Thus, neither the André nor the Wohl et al. scale will not be further considered in this chapter.

The most recent scale for use in an English-speaking sample not selected on the basis of gambling behaviour or proclivity is the 22-item scale proposed by Maltby et al. (2008). Maltby et al. used their scale in a research program focusing on the relationship of the belief in luck to mental and physical health (Day & Maltby, 2003; Day, Maltby & Macaskill, 1999). One notable outcome of the development and use of the multi-dimensional scale in Maltby et al. (2008) was that two separate luck belief dimensions—‘belief in being unlucky’ and ‘belief in being lucky’—were found to be differentially related to health measures. A higher score on belief in being unlucky was quite strongly associated with lower well-being measures whilst a higher score on belief in being lucky was moderately associated with higher well-being measures.

3.1.2 Relating the BIGL12 and BIGL22

Table 3.1 presents the items from the BIGL12, relating them to items from the BIGL22. The scale by Maltby et al. (2008) contains all 12 items from the scale by Darke & Freedman (three of these had slight wording changes), and an additional 10 items. Given the core elements of the original 12-item scale were retained, and new items merely expanded the scale, Maltby et al. (2008) called their ‘new’ 22-item scale the

"Darke and Freedman Beliefs Around Luck Scale". I refer to these two scales as the BIGL12 and BIGL22.

There remains some question about the dimensionality of the items that make up both the BIGL12 and the BIGL22. Darke & Freedman (1997a) found a single factor, Belief in Good Luck, over 12 items that measured a general belief in luck. One item asking about disbelief in luck was reversed coded and included in the global factor. A '13th item' asking about belief in bad luck was excluded from the final scale because of poor factor loading. Maltby et al. (2008) found a different structure. Using Principal Components Analysis, they found a four component solution containing the following: Belief in Being Unlucky, Belief in Being Lucky, Disbelief in Luck, and General Belief in Luck. The BIGL22 expanded on the disbelief in luck item from the BIGL12, and resurrected and expanded on the item asking about belief in bad luck that was dropped from the set of items originally considered for the BIGL12.

In order to examine luck beliefs as an antecedent of lucky feelings and risky choice, it is of fundamental concern to understand the dimensionality. Moreover, in order to examine particular dimensions of belief in luck as moderators of stimuli and feelings or stimuli and choice, it is important to have confidence in the precise item-composition of belief dimensions. There are differences between the BIGL12 and BIGL22 regarding the item count, item content, and factor structure. Although the original BIGL12 was found to have a single factor by Darke & Freedman, the Maltby et al. BIGL22 four-component solution assigned those original 12 items to three different components. The discrepancy of the factor solutions across the two scales is one impetus underlying my validation efforts presently. Another impetus is that the BIGL22 has not been subjected to validation outside of the original published work in which it appeared.

There are several approaches available to scale validation, approaches which accomplish different yet interdependent objectives. The one I take here is to establish different dimensions of luck beliefs and then situate those dimensions in a broader nomological net of logically related constructs, for example superstitious beliefs. An alternative to this approach is to test the predictive validity of the luck belief dimensions with regards to outcome variables. Because my research questions are focused on lucky feelings, and luck beliefs are proposed as a moderator, this second validation approach is inappropriate as a starting point. In order to have confidence in any findings that link luck beliefs to lucky feelings and risky choice, it is first necessary to establish that luck beliefs—independent of outcome variables—are measured with reliability and validity.

There is considerable overlap in the content of items across the BIGL12 and BIGL22. Nine of the original items in the BIGL12 were exactly replicated to the BIGL22. A further three items were only slightly modified. As can be seen in Table 3.1 the primary contribution of the additional ten items in the BIGL22 was to provide a balance across 'good luck' and 'bad luck'. Six new items for Belief in Being Unlucky are a restatement of the six Belief in Being Lucky items with only "good luck" or "lucky" changed to "bad luck" or "unlucky". There were also two new items for Disbelief in Luck that provided a balance between good and bad luck.

3.1.3 Chapter Organisation

I will develop and test two separate Partial Least Squares (PLS) models. The first model is based on items from the BIGL12, and the second is based on items from the BIGL22. The process of developing and testing a PLS model has three basic steps, which are repeated for each model. The first step is a factor analysis to establish unidimensionality of each construct proposed in the model. The second step is an assessment of the measurement model, which focuses on items — individually and as a block — and their relation to both their own construct (convergent validity) as well as their relation to other constructs (discriminant validity). Measurement model assessment also entails statistical significance testing, and verification of internal consistency (i.e., reliability).

Having established the measurement model is of sufficient quality to proceed, the structural model is assessed in the third step. The most basic aspects of structural model assessment are simply examination of β values for paths and the R^2 values for endogenous (i.e., dependent) variables. These are essentially construct-level parameters. They are analogous to regression concepts that are quite straightforward in their application to hypothesis testing. For example, was the path coefficient (i.e., β value) of the expected direction and magnitude? Was the variance explained (R^2 value) of practical significance or at the expected level? Structural model assessment can go beyond these basic regression concepts though, to include model-level parameters, such as total effects, mediation, moderation, Cohen's f^2, Stone-Geisser's Q^2, and a few others that are well beyond the scope of this chapter. I will present and interpret β values, R^2 values, total effects, mediation, moderation, Cohen's f^2 in Sections 3.6 and 3.11.

	BIGL12 Items	BIGL22 Items	
		'Good Luck'	'Bad Luck'
A	I believe in luck.	*same*	-
	Luck plays an important part in everyone's life.	*same*	-
	Some people are consistently lucky, and others are unlucky.	*same*	Some people are consistently unlucky, and others are lucky.
	There is such thing as luck that favors some people, but not others.	There is such a thing as good luck that favours some people, but not others.	There is such a thing as bad luck that affects some people more than others.
B	Luck works in my favor.	*same*	Luck works against me.
	I consider myself to be a lucky person.	*same*	I consider myself to be an unlucky person.
	I consistently have good luck.	*same*	I consistently have bad luck.
	I often feel its my lucky day.	*same*	I often feel like its my unlucky day.
	Even the things I can't control tend to go my way because I'm lucky.	*same*	Even the things in life I can control in life don't go my way because I am unlucky.
	I don't mind leaving things to chance because I'm a lucky person.	*same*	I mind leaving things to chance because I am an unlucky person.
C	It is a mistake to base any decisions on how lucky you feel.	*same*	It is a mistake to base any decisions on how unlucky you feel.
	Luck is nothing more than random chance.	Being lucky is nothing more than random.	Being unlucky is nothing more than random.

Table 3.1: BIGL12 and BIGL22 Items - A side by side comparison of items for the BIGL12 and BIGL22. To the left are indicators for component labels from Maltby et al. (2008): A) General Belief in Luck; B) Belief in Being Lucky items are those in section B under the heading 'Good Luck'. Belief in Being Unlucky items are those in section B under the heading 'Bad Luck'; C) Disbelief in Luck. Items that were retained unaltered from the BIGL12 to the BIGL22 are indicated with "*same*", in the second column. Note the balance across good and bad luck items that results from minimal wording changes to various 'Good Luck' items.

So, as a general overview, I propose and assess two models, using each of the three usual PLS steps just described. The first model focuses on items from the BIGL12 and second model focuses on items from the BIGL22. I use the findings from Part One to cull eight items from the BIGL22 in Part Two. The next section lays out in detail the content of Part One and Two of the chapter, with references to section numbers.

3.1.3.1 Chapter Organisation in Detail

Part One of this chapter focuses solely on items from the BIGL12. In Section 3.2 I determine the factor structure, across multiple datasets, of the items in the BIGL12, resulting in a scale I call the R-BIGL12. In Section 3.3 I specify a model of the nine items from the R-BIGL12 and conduct some initial measurement model tests. In Section 3.4 I specify a model, the R-BIGL12+, which is the nine-item R-BIGL12 combined with the Superstitious Beliefs Scale (Stanovich & West, 1998). In Section 3.5 I perform a measurement model assessment of the R-BIGL12+, and in Section 3.6 I perform a structural model assessment of the R-BIGL12+. Finally, in Section 3.7 I make concluding comments regarding the items in the BIGL12 that will be carried forward to Part Two of this chapter.

Part Two mirrors the general structure of Part One, using 18 items from the BIGL22 collected for a single dataset. Four items from the BIGL22 are dropped at the outset on the basis of conclusions from Part One, so Section 3.8 presents a factor analysis of 18 items from the BIGL22, resulting in a further reduction to 16 items. This 16-item scale is the BIGL16. In Section 3.9, I specify a model of the BIGL16, embedding four constructs inherent to the BIGL16 in a larger model, the BIGL16+, containing cultural background, verbal reasoning, and understanding of randomness. Section 3.10 assesses the measurement model for the BIGL16+. Section 3.11 provides an extended assessment of the measurement model that includes tests of mediation and 'total effects'. Finally Section 3.12 offers concluding comments.

For the convenience of the reader, I provide the following list to consult while reading through the sections described above.

PART ONE: The BIGL12

- Section 3.2: Comparative factor analyses of BIGL12, resulting in the R-BIGL12

- Section 3.3: Specify R-BIGL12 model, with initial measurement model tests
- Section 3.4: Specify the R-BIGL12+ (R-BIGL12 + Superstitious Beliefs)
- Section 3.5: Measurement model assessment of the BIGL12+
- Section 3.6: Structural model assessment of the BIGL12+
- Section 3.7: Part One conclusions

PART TWO: The BIGL22

- Section 3.8: Factor analysis of items from the BIGL22, resulting in the BIGL16
- Section 3.9: Specify the BIGL16+ (BIGL16 + validating constructs)
- Section 3.10: Measurement model assessment of the BIGL16+
- Section 3.11: Structural model assessment of the BIGL16+
- Section 3.12: Chapter conclusions

PART ONE: The BIGL12

3.2 Factor Structure of BIGL12

How many factors[1] underlie the belief in luck, as measured by the BIGL12? Darke & Freedman (1997a) concludes that the BIGL12 measures a single factor. Maltby et al. (2008) found a four factor solution for 22 items, where the original BIGL12 items are

[1] I note that Maltby et al. (2008) used Principal Components Analysis (PCA), whereas Darke & Freedman (1997a) used Principal Axis Factoring (PAF). I will use the generic term 'factor' to refer to both factors and components when discussing results reported in Darke & Freedman (1997a) and Maltby et al. (2008). The choice of technique makes no substantive difference to the outcomes (I ran all of the analyses below using both). However, I report only PAF here because: 1) PCA relies on the relatively more strict assumption that error term variance is either zero or equal over all variables. Thus, a PCA variance explained will also include error variance, inflating that statistic if the assumption isn't met.; 2) Any scale differences in the data can potentially create distortions in PCA. This would be problematic for me because I used a six-point scale for a portion of the data collection. See Tabachnick & Fidell (2001) for a discussion of PCA and PAF.

allocated to three different factors. I now evaluate the factor structure of the BIGL12 across four combined datasets and then test for stability of the factor solutions across datasets. The results of this extensive factor analysis are used to establish unidimensionality of the latent constructs, yielding a revised BIGL12 (R-BIGL12).

3.2.1 Data and Descriptives

There are 425 unique participants used in this factor analysis. Data were collected over three semesters in 2008 and 2009 in my lab, across four different studies. Participants were psychology undergraduates at the University of Sydney. The BIGL12 items were asked at the beginning of each of the studies from which they originate, so could not have been influenced by an experimental manipulation.

The first dataset is from the study presented in Chapter 4. That dataset contains 141 cases, although the study in Chapter 4 contains a total of 154. Thirteen subjects were dropped from the original dataset because they did not complete the superstition scale that is used in this chapter. The remaining datasets are from studies from a separate research programme in my lab that are also interested in luck beliefs. I collaborated with two others in these studies (Bruce Burns and Jonathan Krygier), and the data for these were collected by all three of us. The total number of cases for those datasets is 284. I reiterate that the BIGL12 scale was collected at the beginning of all studies. There are no reasons to believe that the participants systematically differ across data collection occasions.

The individual dataset collection periods were:

- Dataset 1 (n=141): Collected Semester 2 of 2008
- Dataset 2 (n=37): Collected Semester 2 of 2008
- Dataset 3 (n=200): Collected Semester 1 of 2009
- Dataset 4 (n=47): Collected Semester 2 of 2009

Comrey & Lee (1992) establishes sample size suitability for Factor Analysis, concluding that a sample size of 50 is 'very poor', 100 is 'poor', 200 is 'fair', 300 is 'good', 500 is 'very good', and 1,000 is 'excellent'. Based on this advice, Dataset 3 with 200 cases would be at the lower cut-off of 'fair'. I combined Datasets 1, 2 and 4 to form a single dataset containing 225 cases, which is toward the lower end of 'fair'. By combining all 4 datasets together, I create a single dataset with 425 cases, which is about midway between 'good' and 'very good'.

The datasets I will use and refer to for analyses involving the BIGL12 (i.e., Part One; Sections 3.2 through 3.6) are as follows:

- Dataset A (n=200) = Dataset 3
- Dataset B (n=225) = Dataset 1 + 2 + 4
- Dataset T (n=425) = Dataset 1 + 2 + 3 + 4

Datasets A, B and their combination, Dataset T, all provide sufficient sample sizes to conduct factor analytic techniques. To verify the stability of the factor analysis across samples, I will perform a factor analysis on Dataset T, A and B. Comparison of the results should demonstrate any distortions masked in the factor structure of the combined dataset, T. Thus, this routine should provide insight into the extent to which the factor structure is stable across different samples.

In Table 3.2 I report the means and standard deviations for each dataset. Note that the response format for Dataset 1 was a 6-point Likert-type scale ('Strongly Disagree' to 'Strongly Agree'), whereas the others were 5-point Likert scales. This scale difference does not alter the factor solution. In each sample, a higher score indicates stronger agreement. The item number corresponds to the sequence of presentation.

3.2.2 Factor Analysis Results

I conducted a factor analysis on the BIGL12 scale using Dataset T (n=425), Dataset A (n=200), and Dataset B (n=225). Considering the nature of the expected factors, I used oblique rotation[1]. I did not specify the number of factors. Instead I used eigenvalues greater than 1.0 as the cut-off for a factor.

All datasets passed Kaiser-Meyer-Olkin (KMO)'s measure of sampling adequacy and Bartlett's test of sphericity (Dziuban & Shirkey, 1974) for suitability of the data to factor analysis. KMO measures were 0.869, 0.832, and 0.856 for Datasets T, A and B

[1]Maltby et al. (2008) also used an oblique rotation. Factors can be reasonably expected to correlate, justifying an oblique (i.e., non-orthogonal rotation). Oblique rotation produced the clearest loadings for this analysis as well as for Maltby et al. (2008).

	n=200 Scale:1-5		n=141 Scale:1-6		n=47 Scale:1-5		n=37 Scale:1-5	
Item	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
1) Luck plays an important part in everyone's life.	3.26	1.05	3.77	1.36	3.21	1.02	3.14	1.23
2) Some people are consistently lucky, and others are unlucky.	2.68	1.10	3.36	1.47	2.60	1.04	2.62	1.11
3) I consider myself to be a lucky person.	3.02	0.99	3.97	1.19	2.98	1.01	2.86	1.11
4) I believe in luck.	2.87	1.13	3.70	1.46	3.02	1.03	2.86	1.18
5) I often feel it's my lucky day.	2.45	0.99	3.11	1.37	2.49	1.02	2.46	1.17
6) I consistently have good luck.	2.31	0.88	3.11	1.23	2.28	0.93	2.11	0.88
7) It is a mistake to base any decision on how lucky you feel.	4.01	1.07	4.56	1.42	4.02	1.07	3.76	1.16
8) Luck works in my favour.	2.49	0.80	3.23	1.12	2.55	0.90	2.46	0.93
9) I don't mind leaving things to chance because luck works in my favour.	1.84	0.90	2.26	1.07	2.00	0.91	1.89	0.74
10) Even the things I can't control tend to go my way because I'm lucky.	1.88	0.81	2.60	1.15	2.09	0.83	1.92	0.76
11) There is no such thing as luck that favours some people, but not others.	3.41	1.27	4.10	1.49	3.45	1.16	3.22	1.20
12) Luck is nothing more than random chance.	4.01	1.04	4.72	1.30	4.00	1.04	3.92	1.09

Table 3.2: BIGL12 Descriptives for Datasets 1, 2, 3 and 4 - Higher scores indicate stronger agreement.

respectively - all well above the recommended value of 0.6. Bartlett's test outcomes were all significant at $p < .001$ (χ^2 (66) = 2081.67 (Dataset T); = 930.67 (Dataset A); and = 1101.92 (Dataset B)). Factor loadings and percent variance for each factor across each dataset are reported in Table 3.3. Items 2 and 9 yielded problematic loadings in Datasets A and B. I discuss this momentarily.

The factor solutions for all datasets explained considerable variance in the datasets. For each dataset, the first factor explained around 39% of the variance. Across datasets, the second and third factors explained almost equivalent variance ranging from 10% to 14%. The items factored together mostly as expected, with a three-factor solution. I now describe the factors in detail and discuss the factor analytic solutions for each dataset.

Belief in Being Lucky For Dataset T, the first factor was in agreement with Maltby et al. (2008), which they labelled *Belief in Being Lucky*. However, in Dataset B, there is a cross-loading of Item 9 to the factor *Disbelief in Luck*. I posit that Item 9 taps into two different concepts, and thus is a 'double-barrelled' question. To wit, one may believe that luck works in her favour, but mind leaving things to chance. Dataset A also demonstrates a moderately high cross-loading of this item to *Disbelief in Luck*. Item 3 also demonstrates cross-loadings that warrant consideration. There are no apparent content validity issues however, as in the case of item 9. Thus, this item will be retained for the moment, with further inspection at the measurement model assessment.

Disbelief in Luck The second factor emerging from Dataset T corresponds to the Maltby et al. (2008) factor of *Disbelief in Luck*, with the addition of Item 11. This factor emerged in different orders for Dataset A and B. This is unsurprising and no cause for concern given the almost equivalent variance explained for each factor. I note that while drafting the original survey materials I accidentally altered item 11 from its original phrasing (i.e., 'There is such a thing as' to 'There is no such thing as'). This error was propagated throughout all subsequent studies. It appears that in doing so, I may have generated a third item in the factor of *Disbelief in Luck*, at the expense of one item from *General Belief in Luck*. In subsequent analyses I will inspect this item closely (i.e., cross-loadings in PLS) to verify this is the case.

	Dataset T			Dataset A			Dataset B		
Factor →	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
% of Variance →	39.78	13.96	10.67	39.65	12.10	10.48	39.00	14.10	11.44
6) I consistently have good luck.	**0.82**	0.07	0.03	**0.78**	0.03	-0.02	**0.83**	0.12	0.06
10) Even the things I can't control tend to go my way because I'm lucky.	**0.82**	-0.07	-0.07	**0.71**	0.11	-0.16	**0.81**	-0.07	-0.05
8) Luck works in my favor.	**0.78**	0.05	0.09	**0.69**	-0.12	0.05	**0.82**	0.03	0.07
9) I don't mind leaving things to chance because luck works in my favor.	**0.63**	-0.25	-0.08	**0.59**	0.04	-0.21	**0.61**	-0.31	-0.12
3) I consider myself to be a lucky person.	**0.59**	0.21	0.24	**0.71**	-0.14	0.21	**0.55**	0.22	0.30
5) I often feel it's my lucky day.	**0.58**	0.00	0.22	**0.60**	-0.10	-0.06	**0.57**	0.02	0.28
7) It is a mistake to base any decision on how lucky you feel.	-0.02	**0.60**	-0.01	-0.03	-0.01	**0.60**	-0.01	**0.54**	-0.03
11) There is no such thing as luck that favors some people, but not others.	0.11	**0.52**	-0.18	0.02	0.16	**0.41**	0.11	**0.53**	-0.20
12) Luck is nothing more than random chance.	-0.10	**0.51**	0.04	-0.20	-0.07	**0.48**	-0.09	**0.52**	0.05
1) Luck plays an important part in everyone's life.	0.05	0.05	**0.78**	0.17	**-0.84**	0.12	0.07	-0.03	**0.72**
4) I believe in luck.	0.14	-0.08	**0.75**	0.10	**-0.73**	-0.17	0.18	-0.15	**0.70**
2) Some people are consistently lucky, and others are unlucky.	0.00	-0.11	**0.65**	-0.03	**-0.48**	-0.45	-0.03	-0.05	**0.70**

Table 3.3: Factor Analytic Solution for BIGL12 for Datasets T, A and B - Items loading onto a factor in a given column are bolded. Factor names are provided it the discussion.

General Belief in Luck (GBL)		
GBL01	(1)	Luck plays an important part in everyone's life.
GBL02	(4)	I believe in luck.
Personal Good Luck (PGL)		
PGL01	(6)	I consistently have good luck.
PGL02	(10)	Even the things I can't control tend to go my way because I'm lucky.
PGL03	(8)	Luck works in my favour.
PGL04	(3)	I consider myself to be a lucky person.
PGL05	(5)	I often feel it's my lucky day.
Disbelief in Luck (DL)		
DL01	(7)	It is a mistake to base any decision on how lucky you feel.
DL02	(11)	There is no such thing as luck that favours some people, but not others.
DL03	(12)	Luck is nothing more than random chance.

Table 3.4: R-BIGL12 Scale - Item List and Construct Assignment for the 9-item R-BIGL12 Scale. The alphanumeric code to the left (i.e., GBL01) contains identifiers used in PLS models in Figures 3.2 through 3.6. The number in parentheses is the identifier from factor analysis results in Table 3.3.

General Belief in Luck The third factor was in partial agreement with what Maltby et al. (2008) called *General Belief in Luck*, with Item 11 not appearing in this factor for reasons already discussed. Item 2 had quite significant cross-loading to *Disbelief in Luck* for Dataset A. As before, Item 2 appears to be asking about the subordinate belief regarding within-person consistency of luck. Moreover, item 2 asks about consistency of both being lucky as well as unlucky, and so also is a double-barrelled item. That is, I might believe that some people are consistently unlucky, but not consistently lucky.

In summary, I propose that the BIGL12 be reduced by two items. That is, items 2 and 9 should be removed from further analysis. Neither past use nor previous validation efforts of these scales warrant the scale to a standing that requires unquestionable inclusion of these problematic items. I also propose a renaming of Belief in Being Lucky to Personal Good Luck (PGL). Thus, the revised BIGL12 scale (R-BIGL12) that I will use going forward is presented in Table 3.4, along with abbreviations and naming conventions for later PLS modelling.

3.3 The Revised BIGL12 Scale (R-BIGL12)

I now specify a model of the Revised BIGL12 Scale (R-BIGL12) based on the conclusions from the factor analysis in the previous section. That model is presented in Figure 3.2. I propose each path as a hypothesis, and provide a rationale for the path below. I include the Superstitious Beliefs Scale (Stanovich & West, 1998) for a check of the nomological validity (Cronbach & Meehl, 1955), attempting to differentiate between paths that are causal in nature, or merely correlational. Negative relationships proposed between two latent variables are notated as "$\overset{\rightarrow}{-}$". I use Dataset T to test the R-BIGL12 model.

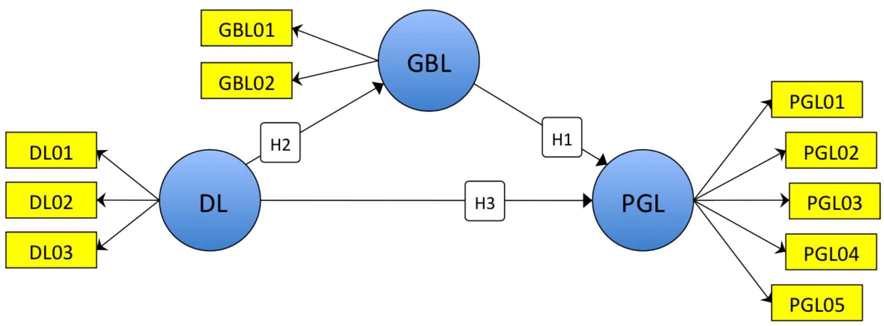

Figure 3.2: Proposed Model for R-BIGL12 - Note that this model contains only the ten items that survived the factor analysis in the previous section. Item content and corresponding numbers (i.e., DL01; DL02; . . .) can be found in Table 3.4.

3.3.1 H1: General Belief in Luck (GBL) $\rightarrow$ Personal Good Luck (PGL)

A general belief in luck (GBL) is broader than a belief in personal good luck (PGL). It might be possible that a person believes that luck exists and plays a role in everyone's life, but not believe that they themselves are lucky per se. However, for a person to believe that he is personally lucky, he must requisitely believe there is such a thing as luck. I assert that GBL would be a necessary but not sufficient condition for PGL, and thus should precede PGL in any modelling arrangement. Therefore, the arrow points from GBL to PGL in the model, indicating GBL is causally antecedent to PGL.

3.3.2 H2: Disbelief in Luck (DL) $\overset{\rightarrow}{-}$ General Belief in Luck (GBL)

For obvious reasons, a disbelief in luck should predict any belief in luck—general or otherwise. Although not borne out empirically in the earlier factor analysis, it might be argued that DL and GBL are unitary from a conceptual standpoint with DL simply being the inverse of GBL. Asserting a causal relationship between DL and GBL is questionable given their conceptual similarity. Closer inspection of the items comprising DL is instructive on this point though.

The items used to measure DL may not be conceptually unidimensional, even though they factored together in Table 3.3. In particular, the item, 'Luck is nothing more than random chance', asks about the relationship of luck and randomness. Alternatively, the item 'It is a mistake to base any decision on how lucky you feel' asks about a person's consideration of luck as an element to be included in decision making; a policy statement of sorts. These would clearly be correlated, but at a fine-grained level may each be predicted differentially by a third construct such as *Understanding of Randomness*[1]. For now, I will retain the factor label and items as supported by the factor analysis of the BIGL12, and will model a three-item DL construct as antecedent to GBL.

3.3.3 H3: Disbelief in Luck (DL) $\overset{\rightarrow}{-}$ Personal Good Luck (PGL)

The rationale for H2 applies equally here: A disbelief in luck should predict any belief in luck—personal or otherwise. If the relationship between DL and PGL is mediated via GBL however, the direct relationship between DL and GBL will be suppressed in the full model. Full mediation would support the view that GBL is causally antecedent to PGL. I will test for mediation as part of H3.

3.3.4 Bootstrap Tests of Significance for H1, H2 and H3

Statistical significance testing in PLS is accomplished using the bootstrap technique that was originally described in Efron & Tibshirani (1993). Bootstrapping is a re-sampling method that can be used to estimate the variance of a given parameter for a dataset. The first step in a bootstrap significance test is to generate n datasets [usually 500 for PLS (Chin, 1998)] by random sampling with replacement from the original dataset. The number of observations in a resample dataset should equal the number of observations in the original dataset. The second step is to calculate the standard deviation

[1] To foreshadow results to come, in Part Two of this chapter, the BIGL22 includes a second item on the relationship between luck and randomness, as well as a second item that asks about basing a decision on luck. The factor analysis there indicates that a 'Luck Is Random' factor emerges, but the 'Luck Policy' factor is unstable.

of a given parameter, for example a bivariate correlation coefficient, across the 500 resamples. The standard deviation of the parameter estimate across the 500 resamples is equated to a standard error, and used to generate a t-value, which corresponds to a given p-value for a given sample size. The calculation of t-values is otherwise no different from the usual operation: $t = \frac{B}{SE_B}$, where B is the unstandardised coefficient and SE_B is the standard error of that coefficient.

As an example of how this works in practice consider an original dataset with an extreme outlier. Random sampling with replacement would generate some resample datasets that do not contain the large outlier, and other resample datasets with multiple instances of the outlier. For a parameter calculated using that outlier, the standard deviation of the resamples would large, relative to an original sample with no extreme outlier. Page 326 in the Appendix to this thesis provides more detail on the bootstrap procedure in particular. The reader will find there a direct comparison of statistical significance testing using SPSS and using PLS: the results are essentially equivalent.

Bootstrap tests were performed on the model in Figure 3.2 using Dataset T with 500 resamples. As can be seen in Figure 3.3, the path between DL and PGL does not reach significance when GBL is included in the model. All other t-values (including item loadings) exceeded the threshold for $p < .001$.

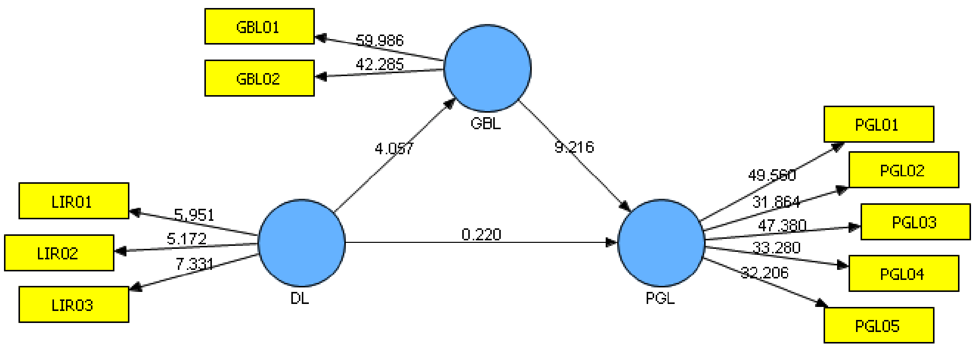

Figure 3.3: PLS Measurement Model for the R-BIGL12 - Bootstrap t-values (500 resamples) for a proposed PLS model of Disbelief in Luck (DL), General Belief in Luck (GBL) and a belief in Personal Good Luck (PGL). The t-values for H2 and H1 paths exceed the threshold for $p < .001$. The t-value for the H3 path does not because of the mediating role of GBL.

The non-significant path from DL to PGL raises the obvious question of whether GBL mediates the relationship between DL and PGL. As a first step, after removing GBL from the model, the t-value of DL $\rightarrow$ PGL becomes 4.136, with a beta value of -0.151. This indicates full mediation. A traditional Sobel Test[1] confirmed this was indeed the case. The full mediation of GBL in the relationship of DL and PGL is the first strong evidence of model-level validity, and is encouraging to see at this early stage in the assessment. Full mediation supports the view that GBL is a mechanism through which DL influences PGL.

3.4 Specification of the R-BIGL12+

I now specify a model where the Revised BIGL12 is embedded with two dimensions of superstitious beliefs. Because I am adding validating constructs to the R-BIGL, I call the resulting model the "R-BIGL12+". (I will use this convention again in Part Two of this chapter, whereby a '+' is added to the BIGL12 model when it is embedded with validating constructs.) The model in Figure 3.4 presents the proposed relationships for R-BIGL12 and superstition constructs.

As before, I propose each path as a hypothesis, and provide a rationale for the path. Also as before, proposed negative relationships between two latent variables are notated as '$\overset{\rightarrow}{-}$'. H1 and H2 are carried forward from the previous model in Figure 3.3. The path from DL to PGL (associated with H3) is omitted in this model, as full mediation via GBL has already been demonstrated. See Table 3.4 and 3.6 for Factor (i.e., Construct) abbreviations and content corresponding to each BIGL12 item label (i.e., items belonging to GBL, PGL, and DL) and superstition item label (i.e., items belonging to LS and AS).

3.4.1 Superstitious Beliefs

In order to establish both convergent and discriminant validity of different dimensions of the belief in luck (i.e., GBL and PGL), I include in this model two factors from the Superstitious Beliefs Scale (Jones & Russell, 1980; Stanovich & West, 1998; Tobacyk & Milford, 1983). Luck and superstition are closely related, but not the same. Fundamental to superstition is a reliance on action, objects or symbols to bring about good fortune or prevent misfortune. Thus, there is an active element to superstition, where

[1]See Preacher & Leonardelli (2011) for an online version of the test. Values for a, b, s_a, and s_b were respectively: -0.229, 0.472, 0.0472, and 0.0505. Full mediation was indicated with $p < .001$.

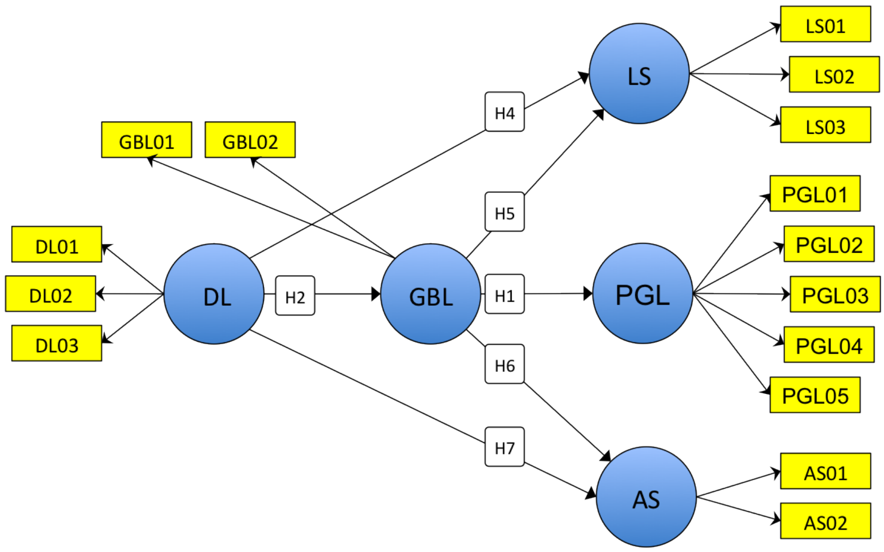

Figure 3.4: Proposed Model for R-BIGL12+ - A proposed PLS model of R-BIGL12 embedded with Astrological Superstitions (AS) and Luck Superstitions (LS). Item content and corresponding numbers for the R-BIGL12 constructs (GBL, PGL, and DL) can be found in Table 3.4. Item content and corresponding numbers for the superstition constructs (LS, AS) can be found in Table 3.6

the focus is on the doing of some action (e.g., crossing fingers), possession of some object (e.g., rabbit's foot), or attendance to some symbol (e.g., astrological birth signs). This is different from belief in luck, which is an acknowledgement or endorsement that good or bad fortune befalls an individual in a deterministic manner. Because superstitious actions have as an intended outcome good fortune (or preventing bad fortune), belief in luck should precede superstition in a causal sense—belief in luck is a necessary but not sufficient condition for superstition.

Stanovich & West (1998) uses nine items to measure a general reliance on superstition in decision making. They demonstrated the scale to predict intelligence and over-reliance on heuristics. I subjected the nine items from this scale to a factor analysis in the same manner as previously with the BIGL12. The nine items can be found in Table 3.6.

All datasets passed KMO's measure of sampling adequacy and Bartlett's test of sphericity (Dziuban & Shirkey, 1974) for suitability of the data to factor analysis. KMO measures were 0.845, 0.796 and 0.854 for Datasets T, A and B respectively - all well above the recommended value of 0.6. Bartlett's test outcomes were all significant at

$p < .001$ (χ^2 (36) = 1066.68 (Dataset T); = 501.44 (Dataset A); and = 613.59 (Dataset B)). Factor loadings are presented in Table 3.5. Two factors emerged from Datasets T, A and B.

The first factor I call Lucky Superstitions (LS) and consists of items SS3, SS4 and SS2. This factor appears to link events, actions, or symbols to being lucky or unlucky. The second factor, I call Astrological Superstitions (AS) and consists of items SS5, SS6. This factor appears to measure beliefs or attitudes regarding the value or instrumentality of astrological information.

Item SS8 is not retained in the scale because it has a low loading (-0.42 for Dataset T) on the LS factor and for Dataset B has a loading on AS that is half that value. Conceptually, there are good reasons it should load across both factors, as it is asking about superstition in general. Item SS1 is also not retained in the scale. It loaded approximately equally, and poorly, across both factors at 0.37 and 0.32 for Dataset T. Item SS7 and SS9 had somewhat low loadings on the AS factor (0.54 and 0.40 respectively for Dataset T), with which it shared no conceptual basis. Item SS7 also cross-loaded heavily in Dataset B. Thus, items SS7 and SS9 are not retained in the scale. The final superstition constructs and items I will use are presented in Table 3.6 in bold font.

3.4.2 H4: Disbelief in Luck (DL) $\overset{\rightarrow}{-}$ Lucky Superstitions (LS)

A disbelief in luck should be causally related to a disbelief in superstitious beliefs that bring about luck. If a person does not believe in luck, then superstitions that bring about luck would necessarily have little meaning.

3.4.3 H5: General Belief in Luck (GBL) $\rightarrow$ Lucky Superstitions (LS)

A general belief in luck should be related to a belief in lucky superstitions. GBL is a necessary but not sufficient condition for belief in lucky superstitions. A person may hold a general belief in luck but not believe in superstitions. This would be the case if a person saw luck as completely uncontrollable.

The relationship between GBL and LS might be attenuated due to what may be idiosyncratic superstitious beliefs, or beliefs from other cultures not represented in these

	Dataset T		Dataset A		Dataset B	
Factor →	**1**	**2**	**1**	**2**	**1**	**2**
% of Variance →	40.79	13.12	39.1	12.76	42.47	13.71
SS3) It is bad luck to have a black cat cross your path.	**0.85**	-0.05	**0.82**	-0.05	**0.82**	0.01
SS4) Opening an umbrella indoors will increase one's chances of misfortune in the near future.	**0.73**	0.04	**0.78**	-0.02	**0.69**	0.10
SS2) The number 13 is unlucky.	**0.72**	-0.07	**0.64**	0.01	**0.80**	-0.12
SS8) I do not believe in any superstitions.	-0.42	-0.08	-0.41	0.00	-0.41	-0.20
SS1) I have personal possessions that bring me luck at times.	0.37	0.32	0.49	0.12	0.36	0.39
SS5) It is advisable to consult your horoscope daily.	-0.03	**0.80**	0.09	**0.79**	-0.12	**0.86**
SS6) Astrology can be useful in making personality judgments.	-0.02	**0.62**	-0.11	**0.80**	0.06	**0.53**
SS7) I have found that talking about successes that I am looking forward to can keep them from happening.	0.04	0.54	0.20	0.31	0.02	0.59
SS9) When something good happens to me, I believe it is likely to be balanced by something bad.	0.00	0.40	0.02	0.25	0.04	0.44

Table 3.5: Factor Analytic Solution for Superstition Scale for Datasets T, A and B - Factor loadings are in bold font. Those items which have low loadings are not retained for use in the R-BIGL12+ Model.

Luck Superstitions (LS)		
LS01	(SS3)	Luck plays an important part in everyone's life.
LS02	(SS2)	The number 13 is unlucky.
LS03	(SS4)	Opening an umbrella indoors will increase one's chances of misfortune in the near future.
Astrological Superstitions (AS)		
AS01	(SS5)	It is advisable to consult your horoscope daily.
AS02	(SS6)	Astrology can be useful in making personality judgments.

Table 3.6: Superstition Constructs and Items - Item List and Construct Assignment for Superstition items. The alphanumeric code to the left (i.e., LS01) contains identifiers used in PLS models in Figures 3.4 to 3.6. The number in parentheses is the identifier from factor analysis results in Table 3.5.

three items, which are concerned with black cats, umbrellas indoors, and the number 13. For example, superstitions Chinese students would be more likely to respond to items that ask about black ravens and the number 4, symbols of bad luck in their culture.

3.4.4 H6: General Belief in Luck (GBL) $\rightarrow$ Astrological Superstitions (AS)

Unlike H5, there is no common luck element shared by GBL and AS. Astrology is often used to provide information about life choices such as compatibility with a romantic partner, or the 'right time' to ask for a raise. These have nothing to do with luck per se. But those who follow astrological advice share a belief in unspecified mechanism that underlies GBL.

3.4.5 H7: Disbelief in Luck (DL) $\underset{-}{\rightarrow}$ Astrological Superstitions (AS)

A disbelief in luck should be related to a disbelief in superstitious symbols such as astrological birth signs. This is relatively weaker proposition that that of DL $\underset{-}{\rightarrow}$ LS because there is no shared component of luck between DL and AS. Even so, a disbelief in luck is likely to reflect the propensity of an individual to disbelieve any claimed association (i.e., birth sign and personality as in AS02) for which there is no plausible mechanism.

3.4.6 Bootstrap Tests of Significance for the R-BIGL12+

Bootstrap tests were performed on the model in Figure 3.5 using Dataset T[1] with 500 resamples. All values exceed t-value threshold for $p < .001$.

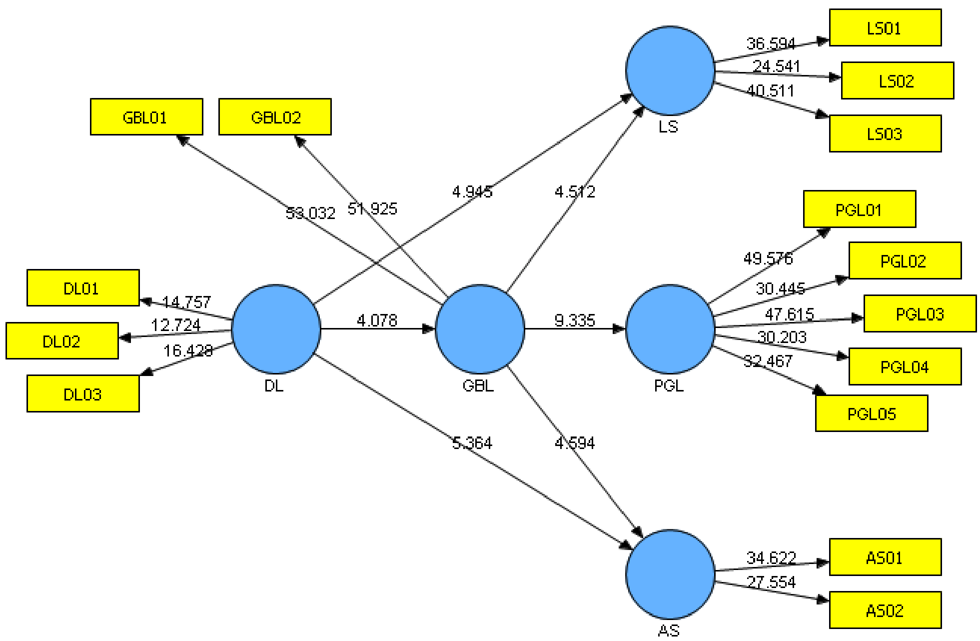

Figure 3.5: PLS Measurement Model for the R-BIGL12+ - Bootstrap t-values (500 resamples) for a proposed PLS model of R-BIGL12 with Astrological Superstitions (AS) and Luck Superstitions (LS). All values exceed the t-value threshold for $p < .001$. See page 326 for explanation of the bootstrap procedure and a table of t-values corresponding to select p-values and degrees of freedom.

I will now proceed with measurement model assessment in order to test for reliability of the items for each latent variable, convergent validity of each latent variable (and its manifest variables), and discriminant validity of each latent variables (and its manifest variables).

[1]Note that Dataset T was used previously testing H1 and H2, so this the t-values for the two paths associated with H1 and H2 are similar to before. The slight differences result only from natural variation in bootstrap estimations.

3.5 Measurement Model Assessment of the R-BIGL12+

There are several tests involved in measurement model assessment. Table 3.7 presents the output of these tests. Before presenting that output, I describe the tests in some detail. Further discussion regarding measurement model assessment can be found in the Appendix.

Assessment of the measurement model aims to verify that the model as specified contains unidimensional and internally consistent blocks of manifest variables (i.e., survey items for a particular construct make up a block of manifest variables), and that those items reliably predict their assigned latent variable with both convergent validity and discriminant validity.

I have already established unidimensionality of each block of manifest variables in the factor analyses above. **Internal consistency** provides an indication that items in a block are homogenous. Internal consistency can be inferred from reliability statistics. In a PLS modelling context, there are two reliability statistics that are commonly used: Cronbach's alpha (Cronbach, 1951, α) and Dillon-Goldstien's rho (Werts, Linn & Joreskog, 1974, ρ_c). The critical values for α and ρ_c are equivalent. A value of 0.70 is considered a minimum[1], whereas a 0.80 is viewed as a more strict minimum threshold recommended for established scales (Hair, Anderson, Tatham & Black, 1998; Nunnally, 1978).

According to Chin (1998), Dillon-Goldstien's rho (ρ_c) is preferable to Cronbach's alpha (α) when conducting PLS analyses. This is because α assumes *tau* equivalence of the indictors; items are given an equal weighting when calculating the α statistic. The ρ_c statistic is computed using the loadings of the items on a construct.

The α statistic will always be less than or equal to ρ_c for any given dataset and block of items. When item loadings do not vary within a block, α and ρ_c will be close. When item loadings vary within a block, α will be less than ρ_c. So, although α is more conservative, ρ_c relies on the same assumption as PLS regarding latent variable creation, and may be seen as more conceptually true to PLS. I will use only Dillon-Goldstien's rho (ρ_c) throughout.

Indicator reliability is a test of the extent to which the variance of an indicator can be explained by a latent variable. It is analogous to a factor loading. The generally

[1]An exception is Bagozzi & Yi (1988), which suggests that 0.60 is acceptable.

accepted threshold is a loading greater than 0.707 (Hulland, 1999). Loadings less than 0.707 are allowable in newly developed scales, or when a block contains a large number of items, but in no case should it be less than 0.40 (Chin, 1998; Falk & Miller, 1992; Hulland, 1999). At values above 0.707, the shared variance between a construct and an indicator exceeds measurement error variance (Bohrnstedt, 1970). The critical value then is whether more than half of an indicator's variance is explained by the latent factor, as opposed to error.

Convergent reliability is inferred when the Average Variance Extracted (AVE) is greater than 0.50 (Fornell & Larcker, 1981). The AVE is a measure of the variance that a latent variable has accounted for in the block as a whole. An AVE of 0.50 means that a latent variable has accounted for, on average, 50% of the variance in a block of items. Note that this 50% cut-off is the same critical value as that underlying the recommendation of 0.707 minimum indicator loading.

The final customary tests in measurement model assessment relate to **discriminant validity**. For an item to exhibit discriminant validity, it should load more highly on its own latent variable than it does on other latent variables (Fornell & Larcker, 1981). Chin (1998) recommends also that a latent variable should attract the highest loadings from its own indicators, in a rank fashion. This can be easily assessed using a 'cross-loadings table', which contains all loadings, for all items, on all latent variables.

Fornell & Larcker (1981) also recommend the comparison of AVE to squared latent variable-latent variable correlations, called a Fornell-Larcker Table. This directly compares the average aggregated item-variance explained by a latent variable to the variance that latent variable shares with other latent variables. The AVE of a latent variable should exceed all squared correlations of that latent variable and other latent variables. In practice, this is quite a low standard, and is usually easily met. An alternative presentation of the Fornell-Larcker Table is to compare the square root of the AVE with the latent variable to latent variable correlations. A rank order comparison can still be made, but the information regarding the latent variable correlations is more easily interpreted, as compared to the squared correlation.

The just-described metrics for measurement model assessment (of the model in Figure 3.4, using dataset T) are reported in Table 3.7. I discuss these in turn below.

Composite reliability (ρ_c) easily exceeds the 0.70 cut-off for all blocks of items, indicating that the blocks are internally consistent. The AVE for all latent variables exceeds

	DL	**GBL**	**PGL**	**AS**	**LS**	$\lvert\bar{XL_i}\rvert$
ρ_c	0.78	0.87	0.91	0.87	0.88	–
DL01	**0.73**	-0.14	-0.07	-0.21	-0.21	0.16
DL02	**0.71**	-0.09	-0.13	-0.25	-0.18	0.16
DL03	**0.76**	-0.21	-0.07	-0.19	-0.21	0.17
GBL01	-0.13	**0.88**	0.46	0.23	0.19	0.25
GBL02	-0.23	**0.88**	0.37	0.27	0.28	0.29
PGL01	-0.10	0.36	**0.86**	0.22	0.11	0.20
PGL02	-0.13	0.34	**0.78**	0.25	0.17	0.22
PGL03	-0.10	0.40	**0.85**	0.21	0.16	0.22
PGL04	-0.02	0.41	**0.80**	0.22	0.10	0.19
PGL05	-0.14	0.42	**0.79**	0.29	0.17	0.26
AS01	-0.28	0.23	0.28	**0.88**	0.42	0.30
AS02	-0.24	0.27	0.23	**0.88**	0.32	0.27
LS01	-0.23	0.22	0.15	0.40	**0.87**	0.25
LS02	-0.19	0.22	0.17	0.28	**0.80**	0.22
LS03	-0.26	0.24	0.12	0.39	**0.86**	0.25
$\lvert\bar{XL_c}\rvert$	**0.17**	**0.27**	**0.18**	**0.27**	**0.21**	–
AVE	**0.54**	**0.77**	**0.67**	**0.77**	**0.71**	–
–	**0.74**	–	–	–	–	–
GBL	-0.21	**0.88**	–	–	–	–
PGL	-0.12	0.47	**0.82**	–	–	–
AS	-0.30	0.28	0.29	**0.88**	–	–
LS	-0.27	0.27	0.17	0.43	**0.84**	–

Table 3.7: Measurement Model Assessment for the R-BIGL12+ using Dataset T - DL=Disbelief in Luck; GBL=General Belief in Luck; PGL=Belief in Personal Good Luck; AS=Astrological Superstitions; LS=Lucky Superstitions. See Tables 3.4 and 3.5 for item content.

Provided at top are Composite Reliabilities (Dillon-Goldstein's rho; ρ_c). In the middle section are item loadings (in bold) and cross-loadings, for each item in the model (item labels are to the left). Vertically down the right side of the middle section, $\lvert\bar{XL_i}\rvert$ is the average of the absolute values of the cross-loadings for a given item. Horizontally across the bottom of the middle section, $\lvert\bar{XL_c}\rvert$ is the average of the absolute values of the cross-loadings for a given construct. In the lower section is the Fornell-Larcker table with AVE's (horizontally in bold), the square root of the AVE (diagonally in bold) and latent variable to latent variable correlations.

the recommended level of 0.50, indicating that convergent validity is acceptable. Indicator loadings all exceed the recommended value of 0.707, supporting the view that the indicators are reliable in their measurement of their assigned latent variables.

As regards discriminant validity, all cross-loadings are below the recommended threshold of 0.50, and in every case items load highest on their own latent variables. The items GBL01 and GBL02 load a little high on PGL (0.46 and 0.37). The items PGL03, PGL04 and PGL05 load a little high on GBL (0.40, 0.41, and 0.42). These cross-loadings are not surprising given the strong correlation between GBL and PGL of 0.47. The Fornell-Larcker table in the bottom section raises no concerns. The square root of the AVE (bolded on the diagonal) easily exceeds the latent variable correlations (both down the column and across the row from the bolded number on the diagonal).

3.6 Structural Model Assessment of the R-BIGL12+

The final structural model is presented in Figure 3.6. All relationships between latent variables are in the expected direction, supporting all hypotheses: H1, H2, H4, H5, H6, and H7; recall that H3 linked DL and PGL, a relationship fully mediated by GBL. To simplify the view of the model, the items are not included. The loadings for each item however, can be found (bolded) in the top section of Table 3.7, above.

Disbelief in luck (DL) is negatively related to general belief in luck (GBL), astrological superstitions (AS) and lucky superstitions (LS). This was predicted in H2, H4 and H7, and indicates that a greater disbelief in luck leads to a lower general belief in luck and lower astrological and luck superstitions.

The relationship of DL to PGL is tested in this model as a 'total effect' path. It is calculated as the product of the two path coefficients between DL and PGL (-0.206 * 0.472) = -0.097. The path coefficients and t-values for all possible 'total effect' paths are automatically provided in SmartPLS. The total effect of DL $\rightarrow$ PGL has a t-value of 3.54, indicating $p < .001$.

A disbelief in luck is associated with reductions of every kind of luck belief or superstitious belief. This is evidence of both construct-level and model-level validity and lends credibility to all constructs in the model.

GBL is positively related to PGL, LS and AS. As predicted in H1, H5, and H6, a general belief in luck predicts a belief that one is personally lucky, one's luck superstitions

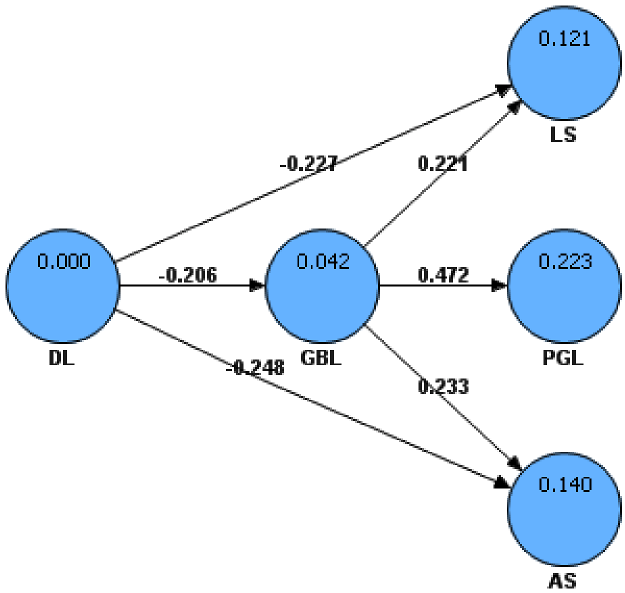

Figure 3.6: PLS Structural Model for the R-BIGL12+ - Parameter Estimates for the R-BIGL12+ (path βs on the lines; R^2 values inside each construct), a proposed model of the R-BIGL12 with Astrological Superstition (AS) and Luck Superstition (LS). Item-construct configurations and item loadings are presented in Table3.7.

and one's astrological superstitions. This again is evidence that the model is hanging together well.

The β value for GBL $\rightarrow$ PGL is quite high at 0.472, while the other five β values are all in a moderate range. The R^2 value for PGL is quite high, at 0.223, indicating that GBL is a good predictor. Removing DL from the model does not alter the R^2 value of PGL. The R^2 value of GBL is low at 0.042. The DL construct is not a very good predictor of GBL in terms of variance explained.

The R^2 values for LS and AS are moderate and about equivalent at 0.121 and 0.140 respectively, but there is a question regarding the source of prediction, given that both DL and GBL predict LS. When DL is the only predictor of LS and AS, the R^2 values are 0.074 and 0.090 respectively. When GBL is the only predictor of LS and AS, the R^2 values are 0.071 and 0.082 respectively. So, there is some shared variance for DL and GBL in LS and AS, but it is mostly unique. (If there were no shared variance between DL and GBL, then the total variance explained in LS and AS should be approximately 0.145 and 0.172 for LS and AS respectively.)

The rationale for H4 and H7 (the paths from DL to LS and AS respectively) were different. A disbelief in luck shared a specific component of the lucky superstitions (luck), whereas the relationship of DL to AS was based only on the broader reliance on a specifiable causal mechanism. Because of these differences, I expected to see weaker support for H7. This was not the case; the β and R^2 values were about equivalent for both LS and AS.

Interestingly, it appears that DL is a better predictor of LS and AS than it is of GBL, using R^2 values as an indicator. The R^2 for GBL, as predicted by DL is only 0.042. Given that two of the three DL items were thought by Darke & Freedman (1997a) to be part of the GBL construct, this is a surprising finding, or rather lack thereof. This warrants closer inspection of the DL construct, which I will provide in Part Two below.

In summary, all hypotheses were supported by the model, with acceptable beta coefficients. In the case of PGL, R^2 was quite high. For LS and AS, R^2 was moderate. For GBL, which was predicted only by DL, the R^2 was quite low. Overall, the model appears to 'hang together' well. As a test of a scale, this analysis has thus far demonstrated a three factor solution for the BIGL12, with ten retained items to be reliable and to have both convergent and discriminant validity. However, DL is the weakest construct in the model.

3.7 Part One Conclusions

Taken together, these results support carrying forward ten items from the BIGL12 to the investigation of the BIGL22. Those are the first ten items in the list below. I also list below the two items I suggest should be removed from the scale[1]. Using those ten items, three factors were found that agree with those in Maltby et al. (2008). The establishment of these three factors in the 12-item scale suggests that the dimensions of luck belief do not require the full 22-item set to emerge. The nomological validity of the three luck belief dimensions is a significant contribution to the understanding of the dimensionality of luck beliefs, and bolsters the confidence in the ten retained items. The ten items listed below had good content validity, and though there was some degree of cross-loading for PGL items onto GBL and GBL items onto PGL, the

[1]Recall that GBL_03 was included in Part One with an erroneous wording. That error was corrected for the dataset used in Part Two.

cross-loadings are not sufficiently high to invalidate the items or the constructs. The additional items proposed in the BIGL22 use the original 12 items and create a balance across 'good' and 'bad' luck. So, having tested the original 12 items, there is already a degree of insight into the additional items from the BIGL22.

General Belief in Luck (GBL)

GBL01: Luck plays an important part in everyone's life.
GBL02: I believe in luck.
GBL03: There is such a thing as luck that favours some people, but not others.

Personal Good Luck (PGL)

PGL01: I consistently have good luck.
PGL02: Even the things I can't control tend to go my way because I'm lucky.
PGL03: Luck works in my favour.
PGL04: I consider myself to be a lucky person.
PGL05: I often feel it's my lucky day.

Disbelief in Luck

DL01: Luck is nothing more than random chance.
DL02: It is a mistake to base any decision on how lucky you feel.

Items not retained

- I don't mind leaving things to chance because luck works in my favor.
- Some people are consistently lucky, and others are unlucky.

PART TWO: The BIGL22

3.8 Factor Structure of the R-BIGL22

For Part Two I use a single dataset collected for a study reported in Chapter 5. In that study, there were a total of 235 participants who were undergraduate students at the University of Sydney. Items from the BIGL22 and validating constructs preceded the experimental manipulation in that study. In Part One above, I concluded that only ten items from the BIGL12 should be retained, and that these ten items belonged to three different dimensions of luck beliefs. Recall that the BIGL22 contains the original 12 items from the BIGL12, plus an additional 10 that provide balance across good and bad luck. For example, 'I consistently have good luck' is complemented by a bad luck item in the BIGL22: 'I consistently have bad luck'.

Indexing the ten items in the list above for a matched bad luck complement (see Table 3.1) locates eight items that I advocate adding into the present analysis. Namely (from the list above): all the items from the PGL construct, all the items from the DL construct, and the GBL03 item. By way of example, PGL01, 'I consistently have good luck' would have a 'bad luck complement' of 'I consistently have bad luck'. The item GBL03 will split into two items. The 'good luck' item is 'There is such a thing as good luck that favours some people, but not others'. The 'bad luck' complement is 'There is such a thing as bad luck that affect some people, but not others'. So, there are a total of 18 items from the original BIGL22 scale that are used in Part Two. These are listed in Table 3.8. I call the resulting 18-item version the R-BIGL22. I have applied the same item labels from Part One above to the R-BIGL22, taking care to parallel the labels and content across to good and bad luck items.

Introduction of the eight items raises some questions. What will become of the factor solution now that these additional eight items are included? Will there still be only four dimensions to luck beliefs? On the one hand, the additional item for Disbelief in luck, 'Being unlucky is nothing more than random' could be reasonably expected to factor together with its lucky complement 'Being lucky is nothing more than random chance'. But looking closely at the PGL dimension—the belief that one is personally lucky—the expected factor assignment is less straightforward.

Five new complementary items appear at first glance to measure a conceptually inverse dimension, PBL, the belief that one is personally unlucky. If PGL and PBL are merely the inverse of one another, then they will be very highly correlated, albeit negatively, and should load onto a single factor. However, these two dimensions could be orthogonal. It may be possible that a person could see himself and both personally lucky in one domain (e.g., love), yet personally unlucky in another (e.g., money).

Another question raised is the presence of the four-item Disbelief in Luck dimension asserted by Maltby et al. (2008). Recall that there were three items in the Disbelief in Luck construct above: from Table 3.8, DL_01; DL_02; and the mis-worded version of

GBL_03. The mis-worded version of GBL_03 has been repaired back to the GBL construct in the data for this study, and there are now two additional items that complement DL_01 and DL_02, for a total of four (the original four from Maltby et al. (2008)) that can be tested for unidimensionality presently. On the basis of content, there is reason to think that these four items might load onto two separate factors. Two items ask about the relationship of luck and chance, and two items ask about the correctness of relying on lucky feelings to inform a decision.

Another question raised by the additional eight items from the BIGL22 is whether the two GBL items, GBL_03 and GBL_04 (see again Table 3.8), will factor into a second dimension. The item GBL_03, and now its bad luck complement GBL_04, while asking about a non-personalised belief in luck, have an emphasis on whether or not luck affects some people in a systematic way. A general belief in luck does not definitionally require that luck be systematic. These two items are more weakly associated with consistency of luck than was the item not retained on the basis of Part One results. Recall that the item 'Some people are consistently lucky, and others are unlucky' was culled in Part One because it loaded equally across the GBL and PGL factors. That equal loading was attributed to a focus on the consistency of luck, rather than the mere existence of luck.

Results of the present factor analysis will be used to address these questions, with the ultimate objective of developing unidimensional constructs for use in the PLS model (BIGL16+) that follows.

3.8.1 Descriptives

The item labels and text of each item can be seen in Table 3.8 along with means and standard deviations for each item. The items used a six-point Likert response format.

Means and standard deviations compare closely to those of the n=141 dataset from Part One, which also used a six-point scale, with one exception: DL_03. Although the standard deviations are nearly equivalent, the mean for DL_03 in the n=141 dataset from Part One (labelled as number seven in Table 3.2) is 4.56, whereas the mean for DL_03 for the present dataset is 2.30, for a difference that is nearly twice the standard deviation of the item. This is taken as evidence of the instability of this item.

Item Label	Item Content	Mean	SD
GBL_01	Luck plays an important part in everyone's life.	3.42	1.49
GBL_02	I believe in luck.	3.29	1.53
GBL_03	There is such a thing as good luck that favors some people, but not others.	2.62	1.34
GBL_04	There is such a thing as bad luck that affects some people more than others.	2.78	1.39
PGL_01	I consistently have good luck.	2.85	1.20
PGL_02	Even the things I can't control tend to go my way because I'm lucky.	2.40	1.18
PGL_03	Luck works in my favour.	2.97	1.20
PGL_04	I consider myself to be a lucky person.	3.59	1.38
PGL_05	I often feel like it's my lucky day.	3.09	1.39
PBL_01	I consistently have bad luck.	2.04	0.96
PBL_02	Even the things in life I can control don't tend to go my way because I'm unlucky.	2.09	0.98
PBL_03	Luck works against me.	2.25	1.00
PBL_04	I consider myself to be an unlucky person.	2.32	1.07
PBL_05	I often feel like it's my unlucky day.	2.58	1.22
DL_01	Being lucky is nothing more than random.	3.78	1.18
DL_02	Being unlucky is nothing more than random chance.	3.64	1.21
DL_03	It is a mistake to base any decision on how lucky you feel.	2.30	1.35
DL_04	It is a mistake to base any decision on how unlucky you feel.	2.39	1.44

Table 3.8: BIGL22 Descriptives- Means and Standard Deviations for 18 items from the BIGL22.

3.8.2 Factor Analysis Results

I used Principal Axis Factoring with Oblimin rotation with factor determination set at eigenvalues greater than 1.0. Four factors were found, as can be seen in Table 3.9. Items are sorted by factor loading, and the set belonging to a factor are bolded together.

KMO's measure of sampling adequacy was 0.910 and Bartlett's test of sphericity was significant at $p < .001$ (χ^2 (153) = 2786.72) indicating the data was suitable for a factor analysis.

I return now to the questions posed above. Firstly, did the PGL and PBL items factor separately? That is clearly answered in the affirmative. The factor correlation for PGL and PBL (recall I ran a oblimin rotation) was 0.312. They are not highly negatively correlated, indicating that they are not merely the inverse of one another. Rather, they are positively correlated. To foreshadow the modelling below, the general belief in luck (GBL) predicts both the belief that one is personally lucky and the belief that one is personally unlucky. I suggest it is the general belief in luck that drives the moderate positive correlation between these seemingly opposite beliefs.

Secondly, Disbelief in Luck did not coalesce as a unitary factor of four items. Two items, DL_01 and DL_02 load high and positively together on a factor that I will call Luck is Random (LIR). Two other items that ask about relying on lucky feelings in decisions load low and negatively with the two LIR items, at to -0.32 and -0.22 respectively. These two items also cross load onto the GBL factor. I conclude that these two items should be dropped from the analyses in this chapter. Thirdly, the four general belief in luck items factored together. From Part One there is evidence that GBL_01 and GBL_02 would suffice without the additional two items. But given the results of this factor analysis, I will retain all four items in the model as I progress through Part Two.

On the basis of the factor analysis above I have culled four items: one each from belief in personal good luck and belief in personal bad luck (i.e., items that contained the stem 'I mind / don't mind leaving things to chance . . . '), and the two items ask about basing a decision on lucky feelings. In addition, I have relabelled Disbelief in Luck to Luck is Random (LIR), indicating that the construct is about the belief one has about the relationship of luck to chance. The revised scale—the BIGL16—has been improved as a result of these changes. It is at the same time more parsimonious and

Factor →	**1**	**2**	**3**	**4**
Percent of Variance (%) →	45.27	12.63	7.34	5.75
Belief in Personal Good Luck (PGL)				
PGL_01 - I consistently have good luck.	**0.90**	0.00	-0.01	0.08
PGL_03 - Luck works in my favour.	**0.80**	0.03	-0.03	-0.01
PGL_04 - I consider myself to be a lucky person.	**0.63**	-0.17	-0.07	-0.22
PGL_02 - Even the things I can't control tend to go my way because I'm lucky.	**0.55**	0.17	-0.10	-0.01
PGL_05 - I often feel like it's my lucky day.	**0.50**	0.12	0.05	-0.24
Belief in Personal Bad Luck (PBL)				
PBL_01 - I consistently have bad luck.	0.04	**0.89**	-0.02	0.11
PBL_03 - Luck works against me.	0.07	**0.85**	-0.00	0.00
PBL_04 - I consider myself to be an unlucky person.	-0.09	**0.82**	-0.00	-0.02
PBL_05 - I often feel like it's my unlucky day.	0.13	**0.57**	0.04	-0.14
PBL_02 - Even the things in life I can control don't tend to go my way because I'm unlucky.	-0.08	**0.55**	-0.14	-0.28
Disbelief in Luck (DL)				
DL_02 - Being unlucky is nothing more than random chance.	0.01	0.01	**0.95**	-0.06
DL_01 - Being lucky is nothing more than random.	-0.07	-0.00	**0.76**	-0.04
DL_04 - It is a mistake to base any decision on how unlucky you feel.	0.02	0.08	-0.32	-0.20
DL_03 - It is a mistake to base any decision on how lucky you feel.	0.01	0.02	-0.22	-0.22
General Belief in Luck (GBL)				
GBL_04 - There is such a thing as bad luck that affects some people more than others.	0.04	0.21	0.02	**-0.70**
GBL_02 - I believe in luck.	0.17	0.00	-0.16	**-0.67**
GBL_03 - There is such a thing as good luck that favors some people, but not others.	0.13	0.16	-0.03	**-0.63**
GBL_01 - Luck plays an important part in everyone's life.	0.31	-0.03	-0.05	**-0.60**

Table 3.9: Factor Analytic Solution for the BIGL22- There four factors that describe 18 items from the BIGL22. Factor labels are provided above each block of items. Item loadings ≥ 0.50 are bolded.

more precise in measurement. A formal explication of the LIR and PBL constructs is now in order, given their inclusion in the BIGL16.

Belief in Personal Bad Luck (PBL) Like the items in PGL, the items in this factor describe a belief regarding the self-relevant relationship of an individual to luck. The slight difference in the wording of PGL and PBL may belie quite a distinction between the two. The belief that one is personally unlucky is not merely the inverse of the belief that one is personally lucky. These two beliefs may be held simultaneously. The belief that one is personally unlucky may be predictive of the risks that a person is willing to take in the face of uncertainty. This is tested in upcoming chapters.

Luck Is Random I have already lent some discussion to this factor or dimension of belief in luck, commenting on its relationship to the general belief in luck. LIR items reflect in a very simple manner the view that there is no distinction between luck and chance.

I now proceed to modelling the BIGL16 in a broader nomological net, pausing first to specify the LIR and PBL constructs that were not included in Part One.

3.9 Specification of the BIGL16+

I resume numbering of hypotheses from the previous section, noting that H1 is carried as equally applicable to the present model as it was the one where it first appeared. For ease of reference, I provide in Table 3.10 the combined list of all items that will be used in the BIGL16+ model. Figure 3.7 presents the BIGL16+ model.

In order to provide some context to LIR, GBL, PGL, and PBL, I include three additional constructs in this analysis. I will refer to this model as the BIGL16+. I first propose two hypotheses that signal the inclusion of PBL and LIR in a model with the luck belief constructs and items carried forward from Part One. I then present the rationale for the inclusion of the three additional constructs: cultural background (Asian); verbal ability (EAT); and understanding of randomness.

Latent Construct	Construct Label	Indicator Label	Indicator Content
General Belief in Luck	**GBL**	GBL_01	Luck plays an important part in everyone's life.
		GBL_02	I believe in luck.
		GBL_03	There is such a thing as good luck that favors some people, but not others.
		GBL_04	There is such a thing as bad luck that affects some people more than others.
Personal Good Luck	**PGL**	PGL_01	I consistently have good luck.
		PGL_02	Even the things I can't control tend to go my way because I'm lucky.
		PGL_03	Luck works in my favour.
		PGL_04	I consider myself to be a lucky person.
		PGL_05	I often feel like it's my lucky day.
Personal Bad Luck	**PBL**	PBL_01	I consistently have bad luck.
		PBL_02	Even the things in life I can control don't tend to go my way because I'm unlucky.
		PBL_03	Luck works against me.
		PBL_04	I consider myself to be an unlucky person.
		PBL_05	I often feel like it's my unlucky day.
Luck is Random	**LIR**	LIR_01	Being lucky is nothing more than random.
		LIR_02	Being unlucky is nothing more than random chance.
Verbal Reasoning	**EAT**	EAT_Score	24-item timed test of verbal reasoning (Esoteric Analogies Test; EAT)
Culture	**Asian**	Any_Asian	What language do you primarily speak at home?
Understanding Randomness	**RQ**	RQ_7	There are no patterns to the outcomes.

Table 3.10: Items Used in the BIGL16+ - Items used in the model are presented here with the construct name, construct label, indicator label, and item content.

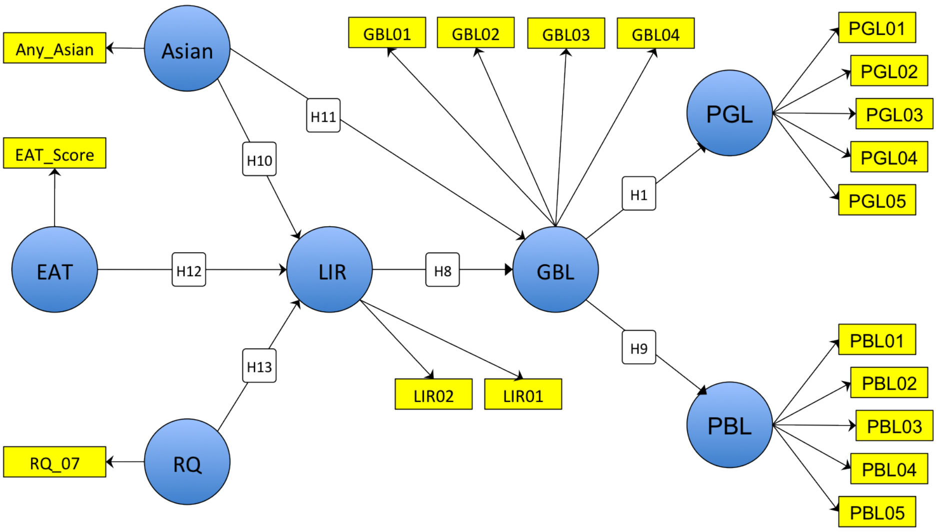

Figure 3.7: Proposed Model for the BIGL16+ - Proposed model of the BIGL16+ which contains four constructs from the BIGL16: Luck is Random (LIR), General Belief in Luck (GBL), belief in Person Good Luck (PGL), belief in Personal Bad Luck (PBL). These BIGL16 constructs are attended by three additional constructs: Cultural Background (Asian), Verbal Reasoning (Stankov, 1997, Esoteric Analogies Test; EAT), and Understanding of Randomness (RQ).

3.9.1 H8: Luck is Random (LIR) $\rightarrow$ General Belief in Luck (GBL)

Wagenaar & Keren (1988) demonstrated that some people make a distinction between luck and chance. Presumably those who endorse luck as "nothing more than random chance" would also tend to endorse a disbelief in luck because a strong conviction that there is no distinction between luck and chance would obviate the belief in luck. On the other hand, a belief that luck is something more than chance indicates a belief in luck, but also a possible causal component to general belief in luck. Thus, relative to the broader construct Disbelief in Luck, Luck is Random is potentially a more potent construct in terms of prediction. That is, it is precisely the belief that luck is 'something more than random chance' that drives a general belief in luck.

3.9.2 H9: General Belief in Luck (GBL) $\rightarrow$ Belief in Personal Bad Luck (PBL)

The rationale here is essentially the same as that of H1. GBL is a broader and more general belief than belief in personal bad luck (PBL). As before with PGL, I assert that GBL would be a necessary but not sufficient condition for PBL, and thus should precede PBL in any modelling arrangement. To explain further, it might be possible that a person believes that luck exists and plays a role in everyone's life, but not believe that they themselves are unlucky per se. However, for a person to believe that he is personally unlucky, he must requisitely believe there is such a thing as luck. Therefore, the arrow points from GBL to PBL in the modelling below, indicating causality.

3.9.3 H10: Cultural Background (Asian) $\overset{-}{\rightarrow}$ Luck is Random (LIR); H11: Cultural Background (Asian) $\rightarrow$ General Belief in Luck (GBL)

As early as 1961, psychological research claimed a cultural difference in belief in luck, skewed to Asians, and the Chinese in particular (Hsu, 1961). A small body of research exists to support these assertions of cultural differences in belief in luck. For example, Liang, Wang, Chen, Feng, Lee, Schwartz, Pasick & Mandelblatt (2008) has found that Chinese-American women get pap smears less frequently than white non-Hispanic American women, partly because of a greater belief in luck. Citing Church (1987) and Weisz et al. (1984), Darke & Freedman (1997a) expected Asian-background participants to more strongly endorse a belief in luck relative to non-Asian-background participants. Darke & Freedman (1997a) found the expected ethnic group differences in the BIGL12. (Asian-American BIGL12 mean of 39.69 versus non Asian-Americans mean of 36.92, t(448) = 2.73, $p < .05$.)

Asian background was measured with a single item asking about the primary language spoken at home[1]. For my measure of "Asian" I included Mandarin, Cantonese, Japanese and any languages from Southeast Asia. I excluded any Indian subcontinent languages.

Based on previous research I propose a negative relationship between having an Asian background and endorsement of statements that indicate no difference between luck and chance (H9). Also based on past research, I propose that having an Asian background will be positively related to a general belief in luck (H10). The causal direction is apparent, but not of substantial interest to me. The objective of including this construct in the model is to examine nomological validity of the BIGL16 items.

[1] All participants could speak and write fluently in English. This was assessed upon their entry to the University of Sydney.

3.9.4 H12: Verbal Reasoning (EAT) → Luck is Random (LIR)

The second construct I add to the model is that of verbal reasoning. I make the plausible assumption that verbal reasoning is a proxy for intelligence. I used the Esoteric Analogies Test (Stankov, 1997, EAT), which asks participants to complete 24 verbal analogies in 4 minutes. (An example item is: GROUND is to FOOT as RAIL is to ____. Participants could select from one of the following: WHEEL – TRAIN – IRON – STATION. The EAT offers a good balance between measurement precision and time required for measurement. The EAT should provide an indication of the role of intelligence in luck beliefs whilst leaving most of participant time to focus on other construct of greater interest to me.

Intelligence should predict accurate understanding of randomness (H11). Intelligence is partly measured by an individual's ability to detect patterns of significant meaning in the environment. Intelligence usually is also thought of as predictive of causal reasoning that is evidence based. Thus it should be through LIR that Intelligence (EAT) has an impact on GBL, a proposition testable through a mediation analysis.

3.9.5 H13: Understanding of Randomness (RQ) → Luck is Random (LIR)

I measured participants understanding of randomness using a single item from a *Randomness Questionnaire* which is under development in my lab. In the questionnaire, participants are asked about the characteristics of a random mechanism. Participants are shown a number of statements and asked to "Please click the one response that best reflects how important that characteristic is for a process to be considered random." Anchors in the response scale were, from 1 to 5: Irrelevant, More likely than not, Somewhat Important, Very Important, Must be True.

The item I use is, 'There are no patterns to the outcomes.' (RQ_07). A number of other items were considered, but there was no simple factor structure, so I chose the item with the greatest content validity. A higher score on item RQ_07 indicates a more accurate understanding of randomness. A faulty understanding of randomness could lead to the belief that luck is something more than random chance (H12). Conversely, a more accurate understanding of randomness should influence an individual's view that chance operates without concern for a person's outcomes, regardless of what label a person uses to describe chance: luck, chance, fate, providence, destiny and so forth.

I now continue to measurement model assessment and structural model assessment of the BIGL16+, having added latent variables for cultural background, verbal reasoning, and understanding of randomness.

3.10 Measurement Model Assessment of BIGL16+

Figure 3.8 presents the BIGL16+ model with bootstrap t-values provided for all indicators and paths. All t-values exceeded the threshold for $p < .001$, except three that only exceeded the threshold for $p < .035$.

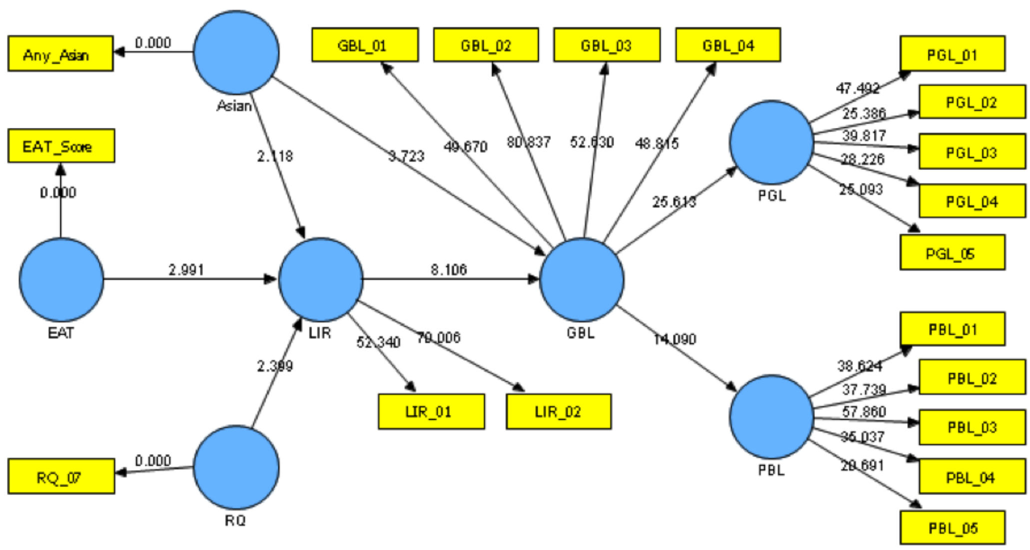

Figure 3.8: PLS Measurement Model for the BIGL16+ - Bootstrap t-values (500 re-samples) for a proposed PLS model of the BIGL16 which contains Luck is Random (LIR), General Belief in Luck (GBL), belief in Person Good Luck (PGL), belief in Personal Bad Luck (PBL). The BIGL16 constructs are attended by three additional constructs: Cultural Background (Asian), Verbal Reasoning (Esoteric Analogies Test; EAT), and Understanding of Randomness (RQ). All t-values exceed the threshold for $p < .035$. All but three exceed the threshold for $p < .001$.

Table 3.11 presents the Composite Reliability, AVE, Item Loadings and Item cross-loadings for the BIGL16+ model. For Asian, EAT and RQ, the Composite Reliabilities, AVE's, and item loadings are 1.0 because these latent variables are measured with a single item. For GBL, LIR, PBL and PGL, Composite Reliabilities and AVE's are all high or very high, and item loadings all exceed the 0.707 threshold, indicating that the items measure their constructs well.

Item cross-loadings between GBL and PGL and between GBL and PBL are quite high, indicating that discriminant validity may be questionable, in particular for the GBL items. I note however that in no case does a GBL item load more highly on another construct, which is the minimum criteria specified by Fornell & Larcker (1981) and Chin (1998). This was the case in the BIGL12 model, and is not surprising given the high latent variable correlations between GBL and PGL (0.75) and between GBL and PBL (0.61). These high construct correlations are likely a result of the purposive sampling, discussed below (as well as in the methods section of Chapter 5), which selected participants from the upper and lower tertiles of a distribution of composite BIGL12 scores.

Table 3.11 also presents the Fornell-Larcker Table for the BIGL16+. The square root of AVE's in every case are greater than the correlation of each latent variable pairing, except for the GBL-PGL and the GBL-PBL pairings. This indicates acceptable discriminant validity for all but the GBL items. On a positive note, PGL and PBL items have acceptable discriminant validity. There is little that can be done about the low discriminant validity of the GBL items in a post-hoc fashion, except to be careful in subsequent modelling to not allow GBL and PGL (or GBL and PBL) to simultaneously predict another latent variable.

Taken together, I am somewhat concerned about the discriminant validity of GBL and PGL as well as that of GBL and PBL. There is indication that discriminant validity is sufficient to proceed, so long as I do not intend to use GBL and PGL (or GBL and PBL) to simultaneously predict some other latent variable.

3.11 Structural Model Assessment of the BIGL16+

I now turn to the structural model assessment and hypothesis testing. Figure 3.9 presents the PLS results for the BIGL16+ model.

3.11.1 BIGL16+ Tests of Hypotheses

Hypotheses 1, 8, 9, 10, 11, 12, and 13 were all supported in the model. Path coefficients were statistically significant and negative in the case of H8 and H10. Path coefficients

	Asian	**EAT**	**RQ**	**LIR**	**GBL**	**PGL**	**PBL**	$\lvert\bar{X}L_i\rvert$
ρ_c	1.00	1.00	1.00	0.93	0.94	0.91	0.92	–
Any_Asian	**1.00**	-0.14	-0.10	-0.18	0.28	0.24	0.19	0.19
EAT_Score	-0.14	**1.00**	0.04	0.21	-0.16	-0.12	-0.11	0.13
RQ_07	-0.10	0.04	**1.00**	0.18	-0.06	-0.05	-0.04	0.08
LIR_01	0.15	-0.15	-0.18	**0.93**	0.44	0.44	0.32	0.28
LIR_02	0.19	-0.24	-0.17	**0.94**	0.45	0.43	0.32	0.30
GBL_01	0.26	-0.17	-0.06	-0.42	**0.87**	0.73	0.46	0.35
GBL_02	0.28	-0.20	-0.06	-0.51	**0.91**	0.70	0.51	0.38
GBL_03	0.24	-0.09	-0.06	-0.40	**0.88**	0.64	0.57	0.33
GBL_04	0.21	-0.11	-0.04	-0.35	**0.88**	0.59	0.60	0.32
PGL_01	0.28	-0.12	-0.07	-0.39	0.59	**0.87**	0.30	0.29
PGL_02	0.15	0.04	-0.07	-0.40	0.57	**0.77**	0.41	0.27
PGL_03	0.15	-0.07	-0.04	-0.41	0.64	**0.88**	0.35	0.28
PGL_04	0.19	-0.16	-0.09	-0.40	0.63	**0.80**	0.23	0.28
PGL_05	0.22	-0.16	0.05	-0.32	0.63	**0.77**	0.43	0.30
PBL_01	0.10	-0.09	-0.02	-0.27	0.43	0.30	**0.86**	0.20
PBL_02	0.23	-0.09	-0.11	-0.36	0.59	0.39	**0.82**	0.30
PBL_03	0.19	-0.05	-0.02	-0.30	0.52	0.38	**0.90**	0.24
PBL_04	0.06	-0.09	-0.02	-0.22	0.42	0.24	**0.84**	0.18
PBL_05	0.18	-0.14	-0.01	-0.25	0.52	0.42	**0.77**	0.25
$\lvert\bar{X}L_c\rvert$	**0.18**	**0.12**	**0.07**	**0.33**	**0.46**	**0.41**	**0.35**	–
AVE	**1.00**	**1.00**	**1.00**	**0.87**	**0.79**	**0.67**	**0.70**	
–	**1.00**	–	–	–	–	–	–	–
EAT	-0.14	**1.00**	–	–	–	–	–	–
RQ	-0.10	0.04	**1.00**	–	–	–	–	–
LIR	-0.18	0.21	0.18	**0.76**	–	–	–	–
GBL	0.28	-0.16	-0.06	-0.47	**0.62**	–	–	–
PGL	0.24	-0.12	-0.05	-0.47	0.75	**0.45**	–	–
PBL	0.19	-0.11	-0.04	-0.34	0.61	0.42	**0.49**	–

Table 3.11: Measurement Model Assessment for the BIGL16+] - See Table 3.10 for construct and item content. Provided at top are Composite Reliabilities (Dillon-Goldstein's rho; ρ_c). In the middle section are item loadings (in bold) and cross-loadings, for each item in the model (item labels are to the left). Vertically down the right side of the middle section, $\lvert\bar{X}L_i\rvert$ is the average of the absolute values of the cross-loadings for a given item. Horizontally across the bottom of the middle section, $\lvert\bar{X}L_c\rvert$ is the average of the absolute values of the cross-loadings for a given construct. In the lower section is the Fornell-Larcker table with AVE's (horizontally in bold), the square root of the AVE (diagonally in bold) and latent variable to latent variable correlations.

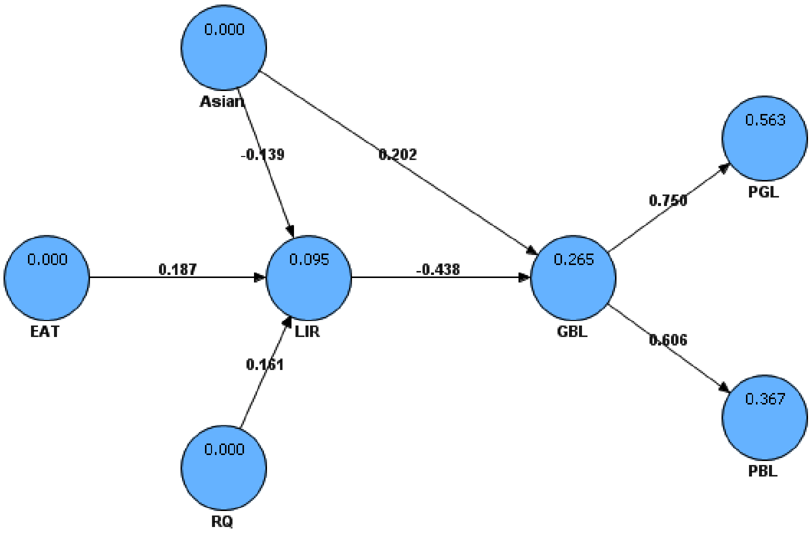

Figure 3.9: PLS Structural Model for the BIGL16+ - Parameter Estimates (path βs on the lines; R^2 values inside each construct) for the BIGL16+, a proposed model of the BIGL16 which contains Luck is Random (LIR), General Belief in Luck (GBL), belief in Person Good Luck (PGL), belief in Personal Bad Luck (PBL). The BIGL16 constructs are attended by three additional constructs: Cultural Background (Asian), Verbal Reasoning (EAT), and Understanding of Randomness (RQ).

were statistically significant and positive for H1, H9, H11, H12, and H13.

The intent of the proposed hypotheses was to validate the luck belief constructs rather than to test a proposed theory, so a detailed review of each of the paths is not necessary. I conclude the luck belief constructs are valid. However, further insight into the structure of luck beliefs can be gained with more in-depth analyses in the following subsections.

3.11.2 Coefficients of Determination (R^2)

The R^2 values for GBL, PGL and PBL are all quite high. The R^2 for GBL is much higher in this model than previously in the BIGL12 (0.265 and 0.042 respectively). This may be partly the result of the addition of Asian, EAT and RQ to the model, and partly the result of the refinement of DL to LIR and the addition of the two new items in GBL. Also, the R^2 for PGL is much higher for this model than the BIGL12+. Though PGL did not change in composition, GBL has.

A more compelling explanation for the dramatic change in values may be the purposive sampling that was used in participant recruitment for the study from which this data came. The primary purpose of that study was to test the effect of a manipulation to induce the feeling of being lucky on dependent variables involving risky choices. Purposive sampling allowed for greater power with a smaller sample size.

I pre-tested the participant pool and disallowed signups from any would-be participants who scored in the (approximately) middle third of the BIGL12 composite scale. This meant that only those who were in (approximately) the highest and lowest tertile of the BIGL12 composite scale participated in the study. I did this knowing that parameter estimates for this sample would not be representative of the population. However, one might argue that a representative sample from the participant pool of undergraduate psychology students would not be representative of the population as a whole regardless of purposive sampling.

This sampling bias was a reasonable trade-off given the uncertainty of the size of the effect of PGL and PBL on downstream latent variables and thus the required sample size. I also had interactions in mind in the design of the study, and so felt it would be an advantage to have the power afforded by purposively sampling participants from the upper and lower end of the distribution of the belief in luck.

3.11.3 Total Effects in the BIGL16+ Model

One characteristic of a good model is that effects propagate throughout the model. I consider now the total effects in the BIGL16+ model[1]. A total effect is the combination of any given paths linking two latent variables. For example, there is a single path from EAT $\rightarrow$ LIR $\rightarrow$ GBL $\rightarrow$ PGL. The total effect is simply the product of all the path coefficients, in this case, 0.187 * -0.438 * 0.750 = -0.062.

In some instances, the total effect between two latent variables will be the combination of paths. For example Asian $\rightarrow$ GBL has both a direct and an indirect path. The coefficient for the direct path, Asian $\rightarrow$ GBL, is 0.202 (see Figure 3.9). The coefficient for the indirect path, Asian $\rightarrow$ LIR $\rightarrow$ GBL is -0.139 * -0.438 = 0.060. Thus, the total effect for Asian $\rightarrow$ GBL is the additive combination of each individual path, 0.202 + 0.060 = 0.262.

Table 3.12 presents the total effect parameter estimates along with their bootstrap t-values. All paths exceed the t-value for $p < .05$, and most exceed the t-value for $p < .01$ level. Some paths however do verge on being practically insignificant. For example, the total path of RQ $\rightarrow$ PBL has a parameter estimate of only -0.04. This indicates latent variables downstream from PBL (in models to come) will be at best only negligibly affected by RQ through the model. Nevertheless, the BIGL16+ does relate — through two intermediating variables — individual differences such as verbal reasoning ability to personal luck beliefs.

3.11.4 Mediation in the BIGL16+ Model

Another characteristic of a good model is that it inheres mediation. Mediation can be thought of as the specification of mechanism. Mediation occurs when the effect of one variable on another operates — either partly or completely — through a third variable. We saw this earlier (Page 79) where the influence of DL on PGL was fully mediated through GBL. Without the presence of GBL, the β from DL to PGL was -0.151 with a t-value of 4.136. As seen in Figure 3.3, with the GBL present, the direct path from DL to PGL was not statistically significant.

[1]Parameter estimates and bootstrap t-values are automatically generated in SmartPLS, for all possible paths.

Path	β value	t-value
Asian $\rightarrow$ GBL	0.26	4.51
Asian $\rightarrow$ PBL	0.16	4.24
Asian $\rightarrow$ PGL	0.20	4.39
EAT $\rightarrow$ GBL	-0.08	2.89
EAT $\rightarrow$ PBL	-0.05	2.69
EAT $\rightarrow$ PGL	-0.06	2.82
LIR $\rightarrow$ PBL	-0.27	6.41
LIR $\rightarrow$ PGL	-0.33	7.14
RQ $\rightarrow$ GBL	-0.07	2.44
RQ $\rightarrow$ PBL	-0.04	2.35
RQ $\rightarrow$ PGL	-0.05	2.42

Table 3.12: Total Effect Parameter Estimates for BIGL16+ - Total effects for direct paths are merely the direct effects found in Figure 3.9 and are thus excluded from this table. Those t-values that exceed 1.97 indicate $p < .05$; t-values that exceed 2.59 indicate $p < .01$; and t-values that exceed 3.33 indicate $p < .001$.

Previously I used a Sobel test for testing for mediation. For complex models, one must decide on whether to leave the three variables embedded in the full model, or isolate them out from the model. According to Iacobucci, Saldanha & Deng (2007), a traditional Sobel test is not permissible when the three constructs are embedded in a structural model and the independent variable and the moderator variable have three or more indicators—which is the case with the present model. I will leave all the variables embedded because I am interested in the model as a whole. The BIGL16+ model has instances of multiple mediation. For example, Asian $\rightarrow$ PGL can be mediated by GBL through two different paths, Asian $\rightarrow$ GBL and Asian $\rightarrow$ LIR $\rightarrow$ GBL. Isolating each triad of possible mediation has the effect of removing other explanatory variables, and so it is possible to inflate the effects — either direct or indirect.

One can speculate with some accuracy when there is full mediation by observing whether a direct effect between two variables becomes statistically non-significant after the addition of the indirect path through the mediating variable[1].

[1]Preacher & Leonardelli (2011, n.p.) has this to say regarding mediation testing: "A variable may be considered a mediator to the extent to which it carries the influence of a given independent variable (IV) to a given dependent variable (DV). Generally speaking, mediation can be said to occur when (1) the IV significantly affects the mediator, (2) the IV significantly affects the DV in the absence of the mediator,

In Table 3.13, I provide a list of all possible mediated relationships in the model, along with the β and t-value for the direct effect path with both the mediator present (see columns 3a and 3b) and with mediator absent (see columns 4a and 4b). Of 11 possible mediated relationships in the model, five have no direct effect so there can be no mediation (although there can still be a total effect, and in fact there is for all paths). Two of the possible mediated relationships are likely to be partially mediated, and four are likely to be fully mediated. This can be inferred by the reduction in the β and t-values for the direct effect, when the mediator(s) is present.

There are several observations that can be made from the information in Table 3.13. Looking first at the top two lines of Table 3.13, when there are no mediators are present, Asian has a direct on PGL and PBL. (As modelled in Figure 3.9, there are two possible mediating paths from Asian to PGL and from Asian to PBL, both of which includes GBL, and only one of which includes LIR.) However, when the mediators are taken into account, the direct effect of Asian on PGL and PBL is diminished to a negligible level. So meditation is highly probable based on this informal, “reduction in β” test.

What happens when LIR is removed from this grouping, leaving only GBL as a mediator? The t-values for the direct path remain unchanged from those for the two paths in column 3b. The reverse is not true when GBL is removed. The β and t-values for direct paths from Asian to PGL and PBL, when LIR is present, do not differ significantly from those values in column 4a and 4b. So, GBL is the mediator in operation for the top two paths in Table 3.13.

What does this mediation mean though? The effect of cultural background (as measured by Asian language spoken at home) on the belief in personal good and bad luck is explainable by the effect of cultural background on a general belief in luck. To put this another way, being from an Asian cultural background has an influence on the beliefs in personal good and bad luck, but only insofar as it has an influence on a general belief in luck. This provides strong support for the model as proposed, and further indication that the dimensionality of luck beliefs has a structural arrangement.

Recall that the Fornell-Larcker Table (Table 3.11) indicated the GBL items had low discriminant validity in relation to the PGL and PBL construct, despite a factor analysis

(3) the mediator has a significant unique effect on the DV, and (4) the effect of the IV on the DV shrinks upon the addition of the mediator to the model. These criteria can be used to informally judge whether or not mediation is occurring, but MacKinnon & Dwyer (1993) and MacKinnon & Dwyer (1995) have popularized statistically based methods by which mediation may be formally assessed.”

1	**2**	**3a**	**3b**	**4a**	**4b**	**5**
		Direct effect		**Direct effect**		**Probable**
Path	**Mediator(s)**	**w/ mediator(s)**		**w/o mediator(s)**		**Mediation**
		β	t-value	β	t-value	
Asian $\rightarrow$ PGL	GBL, LIR+GBL	0.03	0.61	0.17	3.24	Full
Asian $\rightarrow$ PBL	GBL, LIR+GBL	0.02	0.35	0.14	2.28	Full
Asian $\rightarrow$ GBL	LIR	0.20	4.79	0.26	6.38	Partial
EAT $\rightarrow$ GBL	LIR	-0.04	1.10	-0.13	3.10	Full
LIR $\rightarrow$ PGL	GBL	-0.15	2.89	-0.45	8.75	Partial
LIR $\rightarrow$ PBL	GBL	-0.07	1.14	-0.32	4.80	Full
EAT $\rightarrow$ PGL	LIR+GBL	0.03	0.63	0.00	0.04	NDE
EAT $\rightarrow$ PBL	LIR+GBL	0.00	0.02	-0.02	0.29	NDE
RQ $\rightarrow$ GBL	LIR	0.04	0.92	-0.03	0.62	NDE
RQ $\rightarrow$ PGL	LIR+GBL	0.02	0.45	0.04	0.74	NDE
RQ $\rightarrow$ PBL	LIR+GBL	0.01	0.12	0.03	0.39	NDE

Table 3.13: Possible Mediated Relationships in the BIGL16+ - Column 1 lists the beginning and ending construct in possible paths that contain at least one potential mediator. Column 2 lists the potential mediators. Note that some paths have more than one mediator. Refer back to the model in Figure 3.9 to see the configuration. Columns 3a and 3b list the β and t-values (respectively) for the path with all possible mediators present. Columns 4a and 4b list the β and t-values (respectively) for only the direct path with all possible mediators have been removed. Column 5 proposes full or partial mediating based on whether the direct effect with mediators present remains statistically significant. See the footnote on page 110 for explanation, and note in particular the fourth condition listed there. Those t-values that exceed 1.97 indicate $p < .05$; t-values that exceed 2.59 indicate $p < .01$. Paths in the lower block are disregarded, as there is no direct effect.

assigning the items to a separate factor. Perhaps mediation of the Asian $\rightarrow$ PGL and Asian $\rightarrow$ PBL paths reflects discrimination problems inherent to the GBL items? Note however, that EAT has no direct effect on either PGL or PBL (see top two rows on the bottom section of Table 3.13), whereas EAT does have a direct effect on GBL (see row four of the top section). So, concerns about the discriminant validity of the GBL items can be further quelled.

Of the six paths listed in the top section of Table 3.13, only one can be subjected to a traditional Sobel test without any modification of the original model. A Sobel test requires that all three constructs have paths connected them, as was the case in the model in Figure 3.2. Note that the path Asian $\rightarrow$ GBL has both the direct path and the path via the mediator, LIR. The other three paths in Table 3.13 with only a single mediator can be subjected to a traditional Sobel test for mediation without any modification to the model other than inserting a direct path from the IV to the DV. For columns 5 and 6 of Table 3.14, I have removed the path from Asian to LIR and inserted direct paths from Asian to PGL and PBL. (Recall that LIR was not an active mediator based on the "β reduction test".)

Making the necessary alterations to the model, I conducted Sobel tests for each of the six possible paths: the two for which LIR is a potential mediator (i.e., Asian $\rightarrow$ GBL; EAT $\rightarrow$ GBL); the two for which GBL is a mediator for LIR and the personal luck beliefs (i.e., LIR $\rightarrow$ PGL; LIR $\rightarrow$ PBL); and the two for which GBL is a mediator for Asian and the personal luck beliefs (i.e., Asian $\rightarrow$ PGL; Asian $\rightarrow$ PBL). The results are presented in Table 3.14. The result for each path in Table 3.14 concurs with the result for that same path in Table 3.13. Note that any alterations to the model were made only for the test of the path in question, and then the model was returned to the original form.

I have also calculated the variance accounted for (VAF). The VAF is the ratio of the mediated effect to the total effect, and is calculated as $\frac{a*b}{(a*b)+c'}$, where a and b are equivalent to the Sobel test notation, and c' is the direct effect when the mediated path is present. The VAF explains the effect of an independent variable *through a given mediator*, as a percentage of the total effect on a dependent variable in question.

The VAF for the path presented in the leftmost column indicates only a minor portion (24%) of the effect of Asian on GBL is mediated through LIR (Column 1). This is an interesting finding, suggesting that most of the impact of Asian cultural background

		1	**2**	**3**	**4**	**5**	**6**
IV:		**Asian**	**EAT**	**LIR**	**LIR**	**Asian**	**Asian**
Mediator:		**LIR**	**LIR**	**GBL**	**GBL**	**GBL**	**GBL**
DV:		**GBL**	**GBL**	**PGL**	**PBL**	**PGL**	**PBL**
Sobel Test Inputs and Result	a	-0.139	0.187	-0.438	-0.438	0.202	0.202
	b	-0.438	-0.431	0.681	0.572	0.741	0.600
	s_a	0.064	0.059	0.057	0.057	0.055	0.055
	s_b	0.058	0.058	0.042	0.051	0.030	0.046
	$p <$	0.037	0.004	0.001	0.001	0.001	0.001
VAF	a	-0.139	0.187	-0.438	-0.438	0.202	0.202
	b	-0.438	-0.431	0.681	0.572	0.741	0.600
	c'	0.202	-0.041	-0.146	0.071	0.032	0.023
	VAF	23%	66%	67%	78%	82%	84%

Table 3.14: Sobel Tests for Mediation in the BIGL16+ - In the first block are the Sobel test inputs and result for each path. The second block provides the inputs for a Variance Accounted For (VAF) calculation, which estimates the ratio of the mediated effect to the total effect, providing an indication of the strength of mediation. Columns 1 - 4 are modelled in Figure 3.9 with only a single mediator. For columns 5 - 6 the paths contain two possible mediators and the path from Asian to LIR has been removed (see discussion in Section 3.11) because a Sobel test cannot be conducted when there is multiple mediation paths.

is not due to LIR, but due to something else which I have not measured. The VAF's for the other five paths are much higher (ranging from 66% to 84%).

Column 2 examines the path from EAT to GBL, with LIR as a mediator, concluding that mediation is present, and that about 66% of the effect from EAT to GBL is mediated via LIR. In other words, the effect of intelligence (as measured by verbal ability) on a general belief in luck is mostly mediated through the belief that relates luck and chance.

Above, I indicated that the effect of Asian on PGL and PBL was mediated only through GBL and *not* LIR. In light of the mediating role LIR evidenced in columns 1 and 2 of Table 3.14, that previous result should not be taken as evidence that LIR is not an important construct. On the contrary, for EAT and RQ, which are intelligence and knowledge based, LIR is an important construct. This is further support that the validating constructs have demonstrated a nomological validity of the luck belief dimensions.

Looking now to columns 3 and 4, GBL plays an important mediating role in the relationship between LIR and both PGL and PBL. This was already evidenced in a proto-LIR construct seen in Part One of this chapter, disbelief in luck (DL). That earlier mediation is replicated here, although the item content has changed considerably. A disbelief in luck (DL) and a belief that luck is nothing more than random chance (LIR) are very conceptually similar. This is part replication, and part extension of the finding from Part One. Not only is the mediating role of GBL preserved for an alternate luck scepticism construct (LIR), the meditating role is extended to the companion personal belief to PGL, the belief in personal bad luck.

In columns 5 and 6, the mediating role of GBL for Asian and both PGL and PBL is clearly demonstrated to be in agreement with the results of the earlier "reduction in β" test. The VAF's for these two columns are the highest of the six, with one four-fifths of the effect of Asian operating on PGL and PBL via GBL. So, GBL is an important mediator is the model not only for the LIR belief construct, but also the trait-based Asian construct. This is an important insight into the luck beliefs dimensionality and argues strongly for any model of luck beliefs to situate GBL as antecedent to PGL and PBL.

I also note there is a symmetry between PGL and PBL. Even though the PGL and PBL are correlated at 0.42, they appear to have the same antecedents in the model, with very similar parameter estimates. For instance, the VAF's in columns 3 and 4 of Table

3.14 differ by very little in relative terms, and this is the case for the VAF's in columns 5 and 6. When considering only direct effects, the direct effect of Asian on PGL and PBL (without mediators present) is 0.17 and 0.14 respectively and the direct effect of LIR on PGL and PBL (without mediators present) is -0.45 and -0.32 respectively. It remains to be seen whether PGL and PBL will have differential prediction in models to come. That is, will they predict risky choice in the same or opposite directions?

3.12 Chapter Conclusions

Part One of this chapter focused on items from the BIGL12 (Darke & Freedman, 1997a). Two items from the 12-item scale were culled because of content-validity concerns and problematic factor loadings. The shortened form of that scale contained three factors, or dimensions, of luck beliefs: a general belief in luck (GBL); a disbelief in luck (DL); and a belief in personal good luck (PGL)

These three dimensions were embedded in a PLS structural model with two types of superstitious beliefs, a model I referred to as the R-BIGL12+. Measurement model assessment of this R-BIGL12+ indicated that the items had acceptable convergent and discriminant validity. Proposed hypotheses were universally supported, and structural model assessment additionally found a mediating role of GBL in the relationship between DL and PGL. The structural model also revealed that both DL and GBL made unique contributions to variance explained in both lucky superstitions (LS) and astrological superstitions (AS).

Part Two of this chapter mirrored the general structure of Part One, with a focus on 18 items from the BIGL22 (Maltby et al., 2008). A factor analysis found four factors. The GBL and PGL factor from Part One was retained. The disbelief in luck (DL) factor was renamed to 'luck is random' (LIR). A fourth factor, a belief in personal bad luck (PBL) was found. The items in this factor were companion items to those of PGL, with only slight word changes. For example, the PGL item, "I consistently have good luck," was complimented with by the PBL item "I consistently have bad luck."

In addition to the four items culled from the BIGL22 on the basis of Part One findings, two more items were culled due to low factor loadings in the factor analysis in Part Two. The resulting 16-item scale was then embedded in a PLS structural model with verbal reasoning (EAT), cultural background (Asian), and understanding of randomness (RQ), a model I referred to as the BIGL16+.

Measurement model assessment of this BIGL16+ indicated that the items had acceptable convergent and discriminant validity, with one exception. The items forming GBL loaded most highly on GBL, but had quite high cross-loadings onto PGL in particular, and PBL to a lesser degree. The Fornell-Larcker bore this out more clearly. The square root of the AVE for GBL was lower than the absolute values of the GBL-PGL and GBL-PBL correlations. The exceedingly high correlation between GBL and PGL and between GBL and PBL (i.e., path coefficients of 0.75, and 0.61 respectively) explain the cross-loadings, despite a clear factor structure where GBL items loaded onto the PGL factor no higher than 0.31, and PBL no higher than 0.21. The purposive sampling technique used for the sample in Part Two is likely to have contributed to this high correlation, and the consequent low discriminant validity. I conclude that GBL must not be used to simultaneously predict any construct in a model with either PGL or PBL, and call for further research to refine the scale in respect of this.

As in Part One, proposed hypotheses were universally supported in Part Two. Structural model assessment also investigated LIR and GBL as mediators with findings discussed in Section 3.11. The mediation analyses support a structural arrangement of the four luck belief factors, where LIR is predictive of GBL, and GBL is in turn predictive of both PGL and PBL. The direct relationship of LIR to PGL and LIR to PBL is almost completely mediated by GBL. This structural arrangement provides theoretically relevant understanding for each of the luck belief dimensions, and places particular emphasis on GBL as antecedent to PGL and PBL.

A solid understanding of the dimensionality of luck beliefs is critical to understanding the influence of lucky feelings on risky choice. In particular, one type of luck belief (yet not another) may act as a moderator of prior outcomes and lucky feelings.

There are four key outcomes of this chapter, which have been discussed throughout.

1. A confirmation of the factor structure of luck belief items, lending confidence to the composition and dimensionality of belief in luck.

2. The reduction in items, from 22 to 16, forming more parsimonious yet coherent blocks of items for each luck belief dimension.

3. A structural arrangement of luck belief dimensions, yielding understanding of the potential roles of the various luck beliefs.
4. Validation of luck belief dimensions in a nomological net of plausible antecedent constructs, providing further confidence in the factor structure of luck belief items and structural arrangement of luck belief dimensions.

The BIGL16appears to improve on the BIGL12 and BIGL22. The factor structure has been examined across two different analyses. The measures for each factor have good convergent validity. Discriminant validity for GBL could be improved, but for LIR, PGL and PBL, discriminant validity is good. Using superstitious beliefs, verbal reasoning, cultural background and understanding of randomness provided a reasonable nomological net for the latent variables arising from the factor analyses. The BIGL16 provides a strong core for expanded models that include various manipulations and dependent variables of the feeling of being lucky. These models are developed in subsequent chapters.

Chapter 4

Counterfactual Thinking, Lucky Feelings, and Overconfidence

4.1 Chapter Aims and Overview

This chapter has two primary aims. The first is to examine counterfactual thinking as an origin of lucky feelings. The second aim of this chapter is to examine the influence of lucky feelings on overconfidence. For both of these aims, I include positive and negative affect as alternative predictors of lucky feelings and overconfidence.

Counterfactual thinking and affect are by no means isolated concepts. In fact, a prominent topic in the counterfactual literature is that of affect, where affect—usually 'regret' or 'upset'—is often seen as a consequence of counterfactual appraisals[1]. For this reason, I have attempted to integrate counterfactual thinking as an explanation of the origin of lucky feelings with affect as a possible alternative explanation for lucky feelings.

To address the aims of this chapter, I describe and report a study designed to test a counterfactual priming task as a predictor of lucky feelings, and to test the relation of lucky feelings, affect and overconfidence. I first provide an overview of relevant literature. I then present two sets of analyses. The first relates counterfactual thinking,

[1]See Kahneman & Miller (1986) for a number of now-classic examples of the use of affect as a dependent variable in counterfactual appraisals. See Gilovich & Medvec (1995) for a focused commentary on the linkage between affect and counterfactual appraisals. Forthcoming on page 128, I discuss a conceptualisation of luck by Pritchard & Smith (2004) that essentially equates a definition of luck to personal significance of an outcome for which a close counterfactual is salient.

affect and lucky feelings. The second relates affect, lucky feelings and belief in luck to two types of overconfidence.

4.1.1 Counterfactual Thinking as an Origin of Lucky Feelings

The first aim of this chapter is to examine the influence of counterfactual thinking on lucky feelings. Perhaps the most prominent psychological theorising regarding feelings of luck holds that lucky feelings and lucky cognitions arise from 'what if' contemplations. This is reflected in the words of Teigen (1996, p. 156):

> Typically, the most 'lucky' person is the winner who most easily could, or should, have lost, and the most 'unlucky' is the loser who could, or should, have won.

According to Teigen, the feeling of being lucky is closely tied with a subjective assessment of the mutability of the outcome of some event. The more easily imagined that the event could have turned out worse, the more lucky a person *ceteris paribus* should feel. Pritchard & Smith (2004, p. 21) agrees, suggesting that counterfactuals distinguish luck from mere fortune, the former requiring a counterfactual whereas the later does not.

A broad literature on counterfactual thinking preceded Teigen (1996), beginning with the seminal work by Lewis (1973) and pushed along by works such as Kahneman & Tversky (1982, 'Simulation Heuristic'), Kahneman & Miller (1986, Norm Theory), and culminating in a large edited volume (Roese & Olson, 1995a). This body of empirical work on counterfactual thinking was virtually silent on the explicit topic of luck feelings and cognitions[1]. Rather, the focus was on explicating the phenomenon of counterfactual thinking by "identify(ing) empirically the precursors, underlying processes, and consequences of counterfactual thinking..." (Roese & Olson, 1995a, p. 2).

A few studies have attempted to experimentally manipulate the feeling of being lucky to test the impact on lucky feelings and decisions. Perhaps the best example of these is reported in Wohl & Enzle (2003). This study used a 'wheel of fortune' that—depending on condition—either almost landed on bankrupt or almost landed on

[1]By way of example, Roese & Olson (1995a) contains incidental references to 'luck' on only 6 of 408 pages.

jackpot. Results demonstrated that near-loss led to greater feelings of luck and higher levels of gambling, as compared to near-win. The authors did not manipulate counterfactuals per se, but rather the conditions that influenced counterfactual thinking. In that study, counterfactuals co-varied with the experimental condition, but diverged to a degree. Counterfactuals were coded either -1 (near-loss) or 1 (near-win), with the average across the study being -.47. Importantly, this study found that counterfactual direction did not mediate the experimental condition and self-perceptions of luck, nor did it mediate condition and amount gambled. This is a lack of support for most one of the most prominent theories in the area of luck.

In the counterfactual priming task I present in this chapter, I have explicitly elicited counterfactuals with precise instructions regarding those counterfactuals. Thus, while previous studies in the area of luck have looked at the impact of spontaneously generated counterfactuals, I will extend this to consider counterfactuals generated under instruction. The counterfactual priming task began with instructions for participants to write a story. Depending on the condition, participants were asked to write a story about either a lucky, unlucky, positive, or negative event they personally experienced. Then, participants were asked to generate counterfactuals of how the event could have turned out differently. In the lucky and positive condition, participants were asked to generate counterfactuals describing how the event could have turned out worse. In the unlucky and negative conditions, participants were asked to generate counterfactuals describing how the event could have turned out better. Finally, participants were asked to rate counterfactuals with respect to the likelihood or probability of that counterfactual occurring, as well as the impact this counterfactual would have had on the outcome or event.

It is exactly the likelihood and impact of a counterfactual, along with counterfactual direction (i.e., it could have turned out worse), that is thought to drive lucky feelings. Thus, elicited ratings of likelihood and impact in the study reported herein should illuminate the role of counterfactuals in the feeling of being lucky, and provide a good test of the most prominent theory regarding the underlying origin of lucky feelings. The next two subsections provide a discussion of counterfactuals, laying out a framework for different types and measurement considerations.

4.1.1.1 A Typology of Counterfactuals

A counterfactual can take one of eight primary forms arising from a 2 (Downward vs. Upward) x 2 (Internal vs. External) x 2 (Additive vs. Subtractive) matrix (Roese & Olson, 1995b). Each of these components can, at least in theory, be used to predict the nature of the effect of a given counterfactual on decision making or some other dependent variable. The first components of that matrix are whether the counterfactual is downward or upward. That is, a person can think about how things might have been worse (downward) or better (upward). According to theory, it is this downward counterfactual that drives the feeling of being lucky. There is relatively less theory in relation to feelings of being unlucky, but it is plausible that feelings of being unlucky might be driven by upward counterfactuals (thoughts of what nearly was or might have been).

An example of a *downward* counterfactual: Imagine a person who has just won a raffle. As the person was buying the $1 ticket, he found that there was no change in the till to break a $5 dollar note. So, he decided to buy five tickets. The last ticket (of five) given to him turned out to be the winning ticket. A downward counterfactual might be, “Had there been change in the till, I would only have bought one ticket, and thus would not have won the raffle.”

An example of an *upward* counterfactual: Imagine a person who has recently met someone he is attracted to, and that attraction seemed mutual. He wrote the person’s phone number on slip of paper, placing the paper on the dashboard of his car. As he pulled onto the road, the slip of paper flew out of the open window on a gust of wind. (Assume there is no way of getting that phone number again, from say mutual friends.) An upward counterfactual might be: “Had I only put the slip of paper in my pocket, I would be able to call and ask my new acquaintance out on a date.”

In this study, I explicitly requested either an upward or downward counterfactual in the instructions. For the lucky and positive event, I asked for a downward counterfactual. If a participant was in the unlucky or negative condition, I asked for an upward counterfactual.

The second component of the factorial matrix is internal versus external, somewhat analogous to locus of control. That is, a counterfactual may focus on influences that originate within the person or are imposed on the person from the outside environment.

In the first example above, an external counterfactual would be that the person had only a single dollar in his pocket. An internal counterfactual might be that the person didn't buy the extra four tickets because he was not comfortable gambling with more than a single dollar. I did not fix this component in the study; participants were free to generate counterfactuals that are either internal or external.

The third component of the factorial matrix is additive versus subtractive; whether an action was taken (additive) versus whether an action was not taken (subtractive). So, to further the first example above, not buying an additional four tickets in the local raffle is an action not taken. Thus, that counterfactual is downward-subtractive. It is easy to see in the second example, that counterfactuals can be additive or subtractive and accomplish nearly the same effect in some instances. The result is practically the same had the young man put the slip of paper in his pocket (additive), or *not* put the slip of paper on the dashboard (subtractive). I did not fix this component in the study; participants were free to generate counterfactuals that are either additive or subtractive.

Although there are instances where internal versus external[1] and additive versus subtractive[2] might be predictive of some dependent variable, I felt that incorporating such a fine-grained distinction into the design of the experiment was premature for the study at hand. If I were to include the eight factorial permutations of counterfactuals by each of the four conditions of Lucky, Unlucky, Positive and Negative, I would have a design totalling 32 cells. Given the exploratory nature of this study, I chose to allow internal–external counterfactual and additive–subtractive elements to be decided by participants. I limited instructions to only the type of story the counterfactuals were based on and directionality of the counterfactual: Lucky–Downward, Unlucky–Upward, Positive–Downward and Negative–Upward.

One advantage of allowing these two components to be freely chosen by subjects is that it is possible to observe any differences between the types of stories (i.e., Lucky, Unlucky, Positive, Negative) and the nature of the counterfactuals (i.e., additive versus

[1] In the Locus of Control and Causal Attribution literature attributions of outcomes to luck should arise where a person see external forces at play. See Weiner (1974) for one of the earlier proposals of this idea.

[2] See Markman, Lindberg, Kray & Galinksy (2007) for an example of an interesting study on additive versus subtractive counterfactuals. Namely, analytical problem solving is improved with primed subtractive counterfactuals, whilst creative problem solving is improved with primed additive counterfactuals. Additive and subtractive counterfactuals are less well understood in regards to luck.

subtractive and external versus internal). This approach resembles that taken in Study 1 of Wagenaar & Keren (1988). In their study, as in mine, allowing participants to select counterfactuals that are either external or internal and either additive or subtractive provides an opportunity for insights of a descriptive nature.

4.1.1.2 The Degree of Influence of Counterfactuals

Teigen's hypothesis is more narrowly specified than counterfactual direction alone. It is the *closeness* of the counterfactual outcome that determines the degree of feeling lucky (Teigen, 1995): a near-loss produces lucky feelings that are stronger than a far-loss. In the final part of the counterfactual priming task for the study reported herein, participants were asked to rate counterfactuals along two dimensions: the likelihood or probability of a given counterfactual occurring; the impact a given counterfactual would have had on the outcome or event. By including a measure of counterfactual closeness in my study I have a means of testing the counterfactual closeness hypothesis, and comparing closeness with mere direction, in the extent to which the two influence lucky feelings and overconfidence. So, my study differs from (Teigen, 1995) in two important respects. First, I specifically included measures of lucky feelings and overconfidence in the design, and not just ratings for the 'luck' content of elicited stories (see study 1 of Teigen (1995)). Secondly, I include an alternative measure of counterfactual closeness that potentially has greater explanatory power than those used previously in the area of luck.

There have been a few different ways to conceptualise and measure counterfactuals in terms of the amount of influence on decisions. Various terms have been used, and I momentarily provide a discussion of three of these, beginning with *counterfactual closeness*, proceeding to *counterfactual strength* and closing with an extended discussion of *counterfactual potency* and the measures I used in my study reported herein. An overview of these different conceptualisations is relevant to my justification of the usage of counterfactual potency.

Counterfactual Closeness: A clear definition for counterfactual closeness has been elusive (Kühberger, Großbichler & Wimmer, 2011). At least in philosophy, the use of counterfactual closeness, and thus an attempt to define it, dates back to Lewis (1973) which laid out a counterfactual theory of causation. In that work, counterfactual closeness was thought of as the 'likeness' or 'resemblance' of the real world to an imagined one.

Much later Teigen (1995) introduced the term *counterfactual closeness* to the study of lucky feelings. Teigen (1996, Study 3) found a number of factors give rise to the perception of counterfactual closeness in the context of lucky feelings or lucky cognitions. These included whether a person made or was able to make a choice that influenced the outcome, how realistic the counterfactual event was, how much an outcome was deserved, and finally in some instances, physical proximity. In Teigen (1997, p. 320), the concept of closeness is measured as the ease, or probability, that the counterfactual could have occurred: 'Do you think something else could have easily happened?' (1= No, definitely not to 9= Yes, definitely). Included also is a measure of attractiveness of the alternative outcome: 'If something else had happened (i.e., the possibility that you just described) how pleasant or unpleasant would the event have been?'

Counterfactual Strength: In a very recent study in the domain of fairness (Nicklin, Greenbaum, McNall, Folger & Williams, 2011), no definition of counterfactual strength was provided, although a measure of it was used. The measurement was specified as a three item scale (1 = strongly disagree to 7 = strongly agree):

1. If something were done different, this situation would have turned out better.
2. Something could have been done different to result in a more favorable outcome.
3. Something should have been done different to result in a more favorable outcome.

The final item, but not the others, predicted fairness perceptions in the Nicklin et al. study. So, it appears that in this conceptualisation, 'counterfactual strength' is a rating of the co-variation of a more favourable outcome with expectation of an intervention, and not just possibility.

Counterfactual Potency: In another very recent study that was interested in dependent variables of regret, causation and responsibility, Petrocelli, Percy, Sherman & Tormala (2011) proposed a rating of counterfactual likelihood and impact. Recall that in my study I asked participants to rate counterfactuals with respect to the likelihood or probability of that counterfactual occurring, as well as the impact this counterfactual would have had on the outcome or event. Given the similarity of the Petrocelli et al.

(2011) measures to the one I used and their empirical findings, a few comments are in order.

Across four studies, Petrocelli et al. (2011) showed main effects for both the subjective probability of a counterfactual occurring as well as the subjective probability of the counterfactual changing the outcome of an event. They called the subjective probability of a counterfactual occurring the 'If-Likelihood', or *IL*. They called the subjective probability of the counterfactual changing the outcome of the event the 'Then-Likelihood', or *TL*. They termed the multiplicative product of the two 'counterfactual potency', and showed a significant effect—essentially an interaction effect—above and beyond the two main effects.

The If-Likelihood was measured using a nine-point scale with anchors of 'extremely unlikely' to 'extremely likely'. The questions differed depending on the study, but always contained the stem, 'What was the likelihood that. . . '. The response scale differed between their study and mine; I used a six-point scale, which I intentionally chose so there would be no mid-point. Because this was an exploratory measure, I decided that omitting the mid-point might increase the variance in the sample on that item.

The Then-Likelihood was also measured using a nine-point scale with the same anchors. This element differs somewhat between their studies and mine. I conceptualised the counterfactual as having an *impact*, whereas Petrocelli et al. (2011) conceptualised this as a *probability* of a second event occurring that followed the original counterfactual. This conceptual difference is clearly seen by way of examples. Here are the materials for Study 2 of Petrocelli et al., (p. 36):

> One day Sam is on the game show Lets Make a Deal. Sam's options include picking Door #1, Door #2, or Door #3. Behind two of the doors there is nothing. Behind one of the doors is a man who will ask him a trivia question. If Sam picks the correct door, and subsequently answers the trivia question correctly, he will win $50,000. Otherwise, Sam will get nothing. Thus, Sam has to do both things in order to win: pick the correct door and correctly answer the question asked by the person behind the door.
>
> If only Sam had picked Door #2, then he might have won the money. Consider the second part of this thought. That is, given that Sam had picked

> Door #2, what do you perceive was the likelihood that he would have correctly answered the question?

Asking about the probability of a second event makes sense in this context. However, when I designed my materials I imagined an *impact* arising from a counterfactual. That is, a counterfactual if it had occurred could change an outcome to a greater or lesser degree. This is demonstrated in the story and counterfactuals recounted by a participant in my study:

> **[Story]** I went tavelling (sic) through Europe for six months last year. When I was in Slovakia, I would consider it a very lucky encounter, based purely on chance, that we came across a tiny town called Ždiar, in the Atlas mountains. I consider it lucky as we stumbled upon an advertisement for a hostel, one of very few in the area and with little notice, and no forward planning, we found the hostel in the freezing conditions and it turned out to be one of the best places I visited. Great people, great town, great scenery etc etc. I travelled with my sister and although we planned generally a couple of days in advance this was a spur of the moment decision which could've gone either way, luckily enough it was a fantstic (sic) couple of days.
>
> **[Counterfactual 1]** If we had not found the place we had heard about, I would've had a worse few days.
>
> **[Counterfactual 2]** If the people we stayed with had not been so friendly and fun, it would've been a much worse outcome.
>
> **[Counterfactual 3]** If I had not been lucky enough to see the advertisement for the hostel we would not have had the fantstic (sic) time we did.

In Counterfactual 1 and Counterfactual 2, the question of *impact* is directly asking 'How much <u>worse</u> would the few days have been / outcome have been?' Interestingly, the third counterfactual is more consistent with the concept of probability as viewed by Petrocelli et al. (2011) even though it is essentially a restatement of CF1. As these examples show, when a counterfactual is framed with clearly dichotomous possibility (i.e., a fantastic time; answer question correctly), both probability and impact are appropriate. However, when a counterfactual is framed with a continuous outcome (i.e., enjoyment), impact is more appropriate. Impact then seems a more broadly useful rating.

A second difference between the studies in Petrocelli et al. (2011) and my study is the manner in which counterfactual potency is used in the analysis. They use the average of the three calculated counterfactual potencies, and advocate the use of IL and TL as main effects, followed by counterfactual potency in a hierarchical regression. I also use the mean of the three counterfactual potencies, but I use only the product term and not the two 'main effect' terms. It makes little difference to the results, but there is, in my mind, an important conceptual distinction.

For Petrocelli et al. (2011), the objective was to further the theory of counterfactual thinking in tandem with the measurement. Building on the work of Spellman, Kincannon & Stose (2005), they sought to make a contribution to the field that would not disrupt previous theories. I do not share this motivation, and do not view the multiplicative product of probability and impact as an interaction term[1].

Rather, I see the product term in much the same way as I do the two multiplicative products in Newton's 2nd law, $F = ma$. There is no 'main effect' of force, for example, that would explain additional variance when the 'interaction effect' of mass and acceleration are included. My argument is that the product term is irreducible to the individual effects. This is so for counterfactual potency, just as it is for force. In effect, the product term is itself the *definition* of counterfactual potency. Put another way, I challenge the predictive value of a probability of an alternative if it were to have no impact. And, I challenge the predictive value of the impact of a counterfactual if were to have a zero probability. A reading of Pritchard & Smith (2004, p. 18) lends support for my view. They essentially argue that the mere probability of a counterfactual alternative "...will not suffice to capture the core notion of luck." They then refer to the significance of the actual outcome as a second condition required.

[1]By way of disclosure, I note that the inclusion of main effects for probability and impact introduces some challenges to the modelling I perform. Were I to include the main effects with counterfactual potency as an interaction, then any further investigation of counterfactual potency as it interacts with other variables (e.g., belief in luck, which is a logical candidate) would be essentially modelling a three-way interaction. This quickly becomes very complex when yet another variable is included, for example treatment group!

All three conceptualisations of the influence of a counterfactual are intuitively compelling, even if there is some variation in precision among them. Closeness, strength and potency all carry the idea of proximity of an alternate world to the true one. Also intuitively compelling is that as the 'distance' between the alternate world and the true one diminishes, a person would be expected to react more strongly—whether it be feeling more lucky, more fairly treated, or more certain about a candidate for causal explanation. This 'closeness hypothesis' has not been fully examined empirically, which I will do in this chapter and again in the next.

Nevertheless, Petrocelli et al. (as well as my study herein) make a contribution, at least to measurement, by impelling precision in the concept of counterfactual closeness. Returning to the first conceptualisation, counterfactual closeness, Teigen's measure captures the idea of probability of an alternative world eventuating, while the 'attractiveness' question invites the 'impact' question. The product of the probability and impact though is a novel, if not incremental, contribution.

4.1.2 Effects of Lucky Feelings on Overconfidence

The second objective of this chapter is to examine the influence of lucky feelings on overconfidence. Although the overarching interest of my thesis extends beyond overconfidence to include decisions involving risk more generally, overconfidence is a more proximal outcome and is interesting in its own right. I limit investigation of effects of lucky feelings on overconfidence in this chapter. I will examine the influence of lucky feelings on decisions involving risk in Chapter 5.

Simon & Houghton (2003, p. 139) explain that "Overconfidence occurs when an individual's certainty that his or her predictions are correct exceeds the accuracy of those predictions." There is a large body of anecdotes and experimental evidence to suggest that overconfidence can lead to risk in choices, beyond a level that is adaptive.

In an early and widely cited publication by Fischhoff, Slovic & Lichtenstein (1977), overconfidence was operationalised as being certain that answers to general knowledge questions were correct despite providing incorrect answers. As an example of risky choices arising from overconfidence, participants demonstrated a willingness to risk real money on gambles that they wrongly thought were correct. In a survey of small computer company executives Simon & Houghton (2003) found that overconfidence was related to risk taking in product introductions, and that risky product introductions were less likely to achieve success compared to less risky introduction. Overconfident negotiators are more likely to fare worse than realistically-confident ones (Neale & Bazerman, 1985). Disastrous corporate takeovers may be driven in part by overconfidence (Hiller & Hambrick, 2005; Roll, 1986). Negative returns resulting from excess entry into an industry arise in part from an expression of overconfidence, being underestimation of competitors' abilities and the hyper-competition that results from many overconfident entrants (Camerer & Lovallo, 1999). And especially for tasks and situations involving personal perceived control, individuals discount the probability of aversive outcomes with detrimental personal outcomes (Goodie, 2003; Greening & Chandler, 1997; Weinstein & Klein, 1996).

Determining the extent to which overconfidence results from lucky feelings might help to clarify the relationship of lucky feelings to risky choice. Feeling lucky might lead a person to be less comfortable with risk, as would be consistent with the *mood maintenance hypothesis* (Isen & Patrick, 1983), where preservation of a positive mood is prioritised over potential gains to be had from risk taking. However, I suggest that feeling lucky should result in an underestimation of risk due to overconfidence, and therefore probably to an increase in risk tolerance. The everyday concept of good luck inheres an element of imperviousness, or at least a benevolence of chance. To say that one 'feels lucky' may say something about a probable or hypothetical outcome relative to a distribution of possible outcomes, with a skew toward the positive tail.

There are many questions about the relationships of feeling lucky to risk taking. Investigating overconfidence empirically as a dependent variable of lucky feelings is a starting point, and may provide insight into the extent to which overconfidence may be one mechanism through which lucky feelings have an influence on risk tolerance in decision making involving uncertainty.

4.1.3 Three Types of Overconfidence

Overconfidence is not a unitary concept. Three types, or categories, of overconfidence have been identified (Moore & Healy, 2008): overestimation, overplacement, and overprecision. I define and discuss each of these in turn.

Overestimation Overestimation occurs when an individual makes an overly optimistic prediction regarding his or her objective level of performance. For example, one might predict a 5km race time of 20 minutes, but have an actual time of 22 minutes. Underestimation then, is the inverse; when an individual makes an overly pessimistic prediction regarding his or her objective level of performance. I use the term *Overestimation* herein as inclusive of both over- and under-estimation. For the sake of ease in analyses and reporting, underestimation will be coded as a negative overestimation.

Overplacement Overplacement on the other hand occurs when an individual makes on overly optimistic prediction regarding his or her performance relative to others. For example, one might predict finishing a 5km race among the top 20 competitors, but actually places lower. Underplacement then, is the inverse; when an individual makes an overly pessimistic prediction regarding his or her performance relative to others. I use the term *Overplacement* herein as inclusive of both over- and under-placement. For the sake of ease in analyses and reporting, underplacement will be coded as a negative overplacement.

Overprecision Overprecision can be thought of in terms of an overly narrow confidence interval. Many classic studies from the overconfidence research of Kahneman and Tversky measured overprecision by eliciting—for example, "...the lowest and highest estimates such that you are 90% confident your estimate falls within that range". Alternatively, a participant might be asked the probability that his or her response is correct. Because overprecision involves probabilities, it can only be meaningfully conceptualised at the group level[1]. If fewer than 90% of participants in a sample are correct, then the participants—as a group—are thought to be overprecise.

These three different types of overconfidence have been shown to influence different types of risk choice. In a study by Merkle (2011) in a financial investing context, overplacement is associated with a view that one is better informed, more experienced and more skilled, relative to the market. Overestimation is associated with the view

[1]An individual can only be correct or incorrect for a single item or sum of items, but a group of people provide a distribution, or proportion, from which probabilities may be inferred at the group level. However, if an individual's confidence ratings for a number of items are collected, then

that one's portfolio is less risky than it actually is in terms of volatility as well as average returns. Both overprecision and overestimation are associated with a lack of portfolio diversification. The three types of overconfidence are related in a systematic way. Overprecision tends to inflate both overestimation and overplacement, because it reflects a misunderstanding of the true probability distribution of possible outcomes. When there is better precision, better estimates of absolute and relative performance follow (Moore & Healy, 2008).

Overestimation, overplacement and overprecision can occur prior to a task. They can also occur after a task when there is incomplete information regarding actual objective and relative performance. For the trivia task completed by participants on the study described below, I provided no feedback regarding the number of trivia questions answered correctly. Even though the trivia questions were very difficult, guessing could have gotten a correct answer. So any feelings of optimism that arise from either feeling lucky or positive affect might influence objective estimates. The same could be true for pessimism and unlucky feelings or negative affect. I also provided no information regarding the relative performance of others in the study, and post-task estimates of overplacement could potentially be influenced by the treatment condition of participant.

A further element of overestimation and overplacement is important to take into account given the task used in the study described momentarily. This is the interaction of task difficulty and these two types of overconfidence. Namely, for difficult tasks (which characterises the task I use), people will on average overestimate and underplace their performances. This holds for assessment of past performance, but not for prior assessment when task difficulty is not known. I discuss the implications of this pattern for my results later.

4.1.4 The Relationship of Affect with Lucky Feelings

Another objective of this chapter is to clarify the relationship of affect and lucky feelings with respect to a third, dependent variable. Affect and lucky feelings could inter-relate in a number of different ways that I am able to examine with the study reported herein. It is important to clarify expectations of what is possible, as well as what is explicitly sought in terms of a model that represents the data most parsimoniously. I now lay out the types of relationships that affect and lucky feelings may have with each other and a dependent variable. This discussion is meant to sensitise the reader to the possibility of various possible configurations of the inter-relationships in order to facilitate discussion of the final models.

In Figure 4.1 I present graphical representations of five classes of possible inter-relationships of affect and lucky feelings that I considered in the design of the study reported in this chapter. I have simplified the relationships of affect and lucky feelings in Figure 4.1 by laying aside for the moment the valence of affect (i.e., positive or negative). Each sub-figure is discussed below.

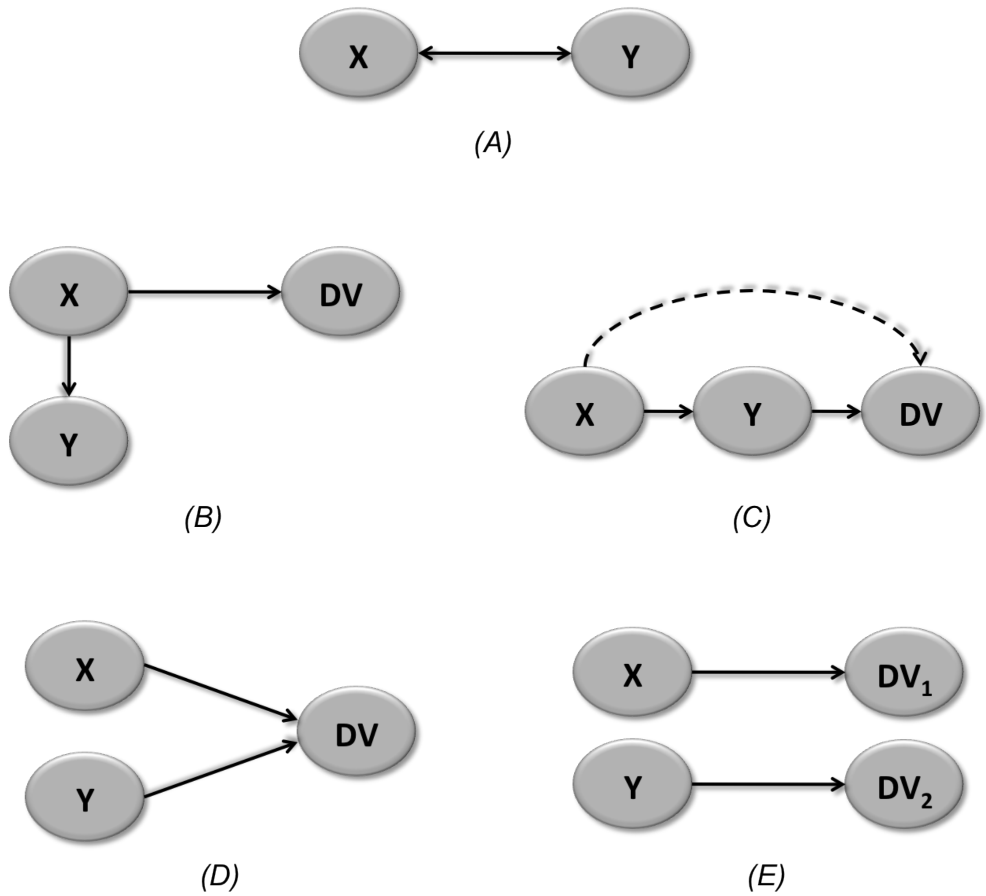

Figure 4.1: Possible Relationships Between Affect and Lucky Feelings - X and Y may be either affect of lucky feelings. Sub-figures (A) through (E) present possible classes of inter-relationships between affect, lucky feelings and dependent variables.

(A) Represented in sub-figure A, the most sceptical view of lucky feelings would hold that affect and lucky feelings are merely two different words that describe the same phenomenon. This would be demonstrated with a very high correlation between the two measures, or experimentally by indistinguishable effects arising from a manipulation[1].

(B) Represented in sub-figure B, where X = Affect and Y = Lucky Feelings, lucky feelings might merely arise from affect and have no influence on any dependent variable(s). In other words, lucky feelings might be nothing more than an epiphenomenon. Of course, the alternative arrangement is possible where X = Lucky Feelings and Y = Affect. However, the precedence of the study of affect over lucky feelings, and the multitude of empirical results that demonstrate affect influences dependent variables of interest, would argue in principle and practice against an arrangement of lucky feelings predicting affect.

(C) Represented in sub-figure C, where X = Affect and Y = Lucky Feelings, is the possibility that lucky feelings serves as a partial or complete mediator for the influence of affect on some dependent variable. Of the sub-figures presented here, I considered this as one of the more likely empirical results. The alternative configuration, where X = Lucky Feelings and Y = Affect, was less compelling to me given that affect is definitionally a more primal emotion than lucky feelings[2]. At the very least, affect is a broader characterisation of internal state or drive, whilst the feeling of being lucky is a more narrow one.

(D) Represented in sub-figure D, where X = Affect and Y = Lucky Feelings, affect and lucky feelings may have unique influence on the same dependent variable.

(E) The final class of relationships I considered is represented in sub-figure E, is one of double-dissociation. Simply put, affect and lucky feelings have unique influence on different dependent variables.

[1] I note that results of Study 2 from Wohl & Enzle (2003) argue against (A). That study found that affect did not differ across treatment groups, although all other measures, including their measure of lucky feelings did differ across treatment groups.

[2] I note for example that Paul Ekman's classic faces contained basic affective displays, and 'Lucky' was not among them.

4.2 Method

The study can be thought of in two stages. Stage 1 consisted of surveys and the counterfactual priming task. Stage 2 consisted of a trivia task, including estimates of performance before and after completing the trivia questions. Details for each part of the study will be discussed in sections below. A graphical overview of the study is presented in Figure 4.2. In that figure Stage 1 is along the top, and Stage 2 is along the bottom.

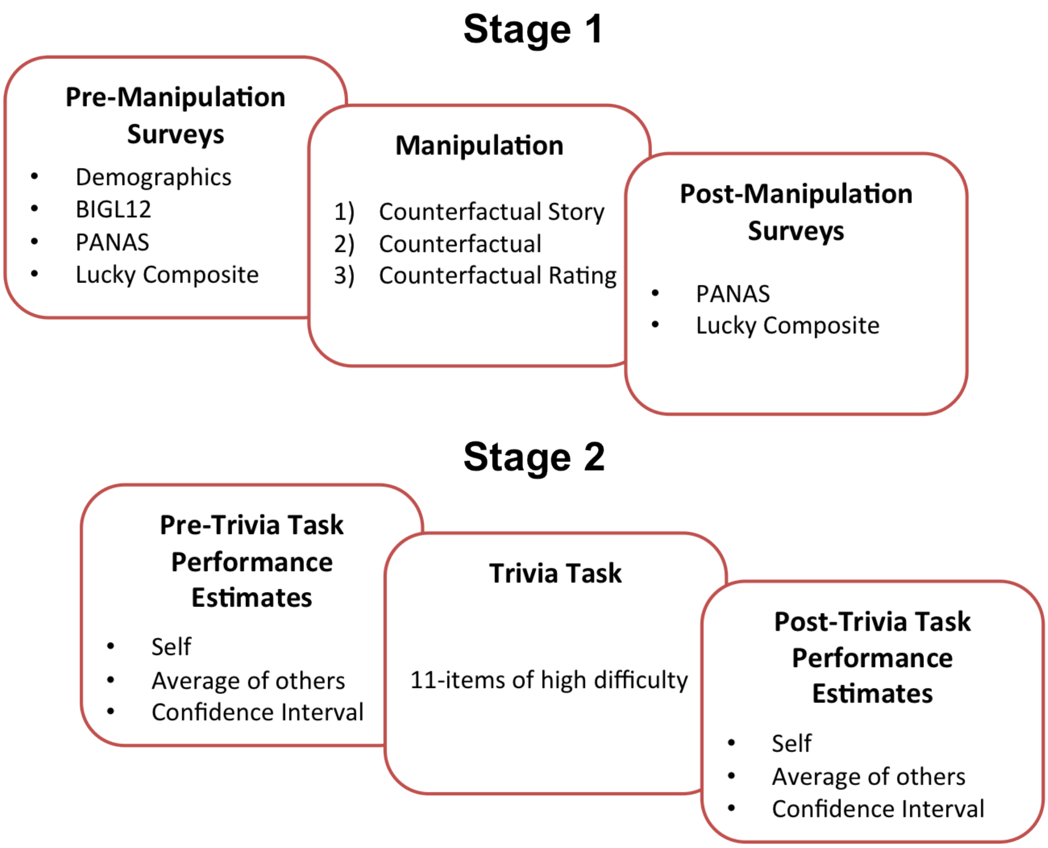

Figure 4.2: Procedure Overview for the Counterfactual Priming Study - Stage 1 consisted of surveys and the counterfactual priming task, represented along the top row. Stage 2 consisted of the Trivia Task, represented along the bottom row.

In the first part of the study, participants were welcomed into the lab, provided an introduction to the study, completed consent forms, and logged onto a computer. Participants then completed approximately 10 minutes of surveys. Following these surveys, participants were allocated to one of four conditions: Lucky; Unlucky; Positive;

and Negative. Participants then were requested to write about an event they personally experienced, where the nature of the event corresponded to their condition. When they had finished writing about the event, they were requested to generate counterfactual statements about the story previously written. These counterfactuals were displayed back to the participants and they were asked to rate the likelihood and hypothetical impact of the counterfactual statements they had previously generated. Participants then completed a subset of the surveys they had completed at the beginning of the study, namely the PANAS and the Lucky Composite.

In the second part of the study, participants provided estimates of their performance on an upcoming trivia task. They then completed the trivia task and provided estimates of their performance of the immediately preceding trivia task. If there was time remaining in the allotted hour, participants then completed a brief and unrelated study. Finally, participants were debriefed, and then left the lab.

4.2.1 Sample and Equipment

A total of 154 undergraduate psychology students at the University of Sydney participated in the study for extra credit. The study was approved by the University of Sydney Human Research Ethics Committee (HREC Approval #11609). Participants signed up for the study via a university sponsored portal. I wanted to prevent participants from knowing the study was about luck, and so provided a vague description. The study was advertised under the short title of "Conditions Affecting Decision Making". A short brief followed which said:

> What's YOUR story? What does your story have to do with the way you make decisions? This study asks you to write a brief story about a recent event and then answer a few questions, including some trivia!

All materials were delivered on 19 inch LCD monitors via Windows Internet Explorer using javascript and html. On average, the study lasted approximately 45 minutes.

4.2.2 Pre-Manipulation Measures

Participants were asked to complete some basic demographic questions including gender, language spoken at home and age. These questions were followed by three[1] scales: the BIGL12; the PANAS Scale; and a four-item luck composite scale. The BIGL12 (Darke & Freedman, 1997a) was presented and discussed in Chapter 3, and the items are listed there in Table 3.1 on page 69. In the modelling below, I use the 5-item PGL construct as refined in that earlier chapter.

The PANAS (Watson et al., 1988, Positive and Negative Affect Scale) consists of 20 items that measure positive and negative affect. Although I collected data for the entire scale, I use only responses corresponding to the subset of the original PANAS found in the shorter 10-item form[2], the I-PANAS-SF (Thompson, 2007, International PANAS Short Form). The I-PANAS-SF was developed for use in cross-cultural applications as well as to reduce the length of time required for measurement.

In PLS modelling, latent constructs usually perform better when specified with between three and six items. The greater the number of items, the more likely it is that indicators will have a loading onto a latent construct that is lower than the recommended level of 0.70. Although this is acceptable, it is not preferable (Vinzi, Chin, Henseler & Wang, 2010, p. 685; 695). I also could calculate the mean of the 10-items for positive affect and the mean of the 10-items for negative affect, but this would provide only a single indicator, which is usually considered poor modelling technique because item-level variance is discarded unnecessarily. Only items from the shorter I-PANAS-SF scale are therefore used in the analyses below.

The Luck Composite Scale is inspired by Wagenaar & Keren (1988). They propose 12 scaling dimensions that were selected based on ‘lengthy discussions with over a hundred gamblers’ (Wagenaar & Keren, 1988, p. 68). In the first study, participants judged one luck story and one chance story, and rated them both on each of the 12 proposed dimensions. There were a total 40 luck stories and 40 chance stories, and each story was judged by 5 participants. Wagenaar & Keren (1988) conducted a discriminant

[1]For use in analyses in Chapter 3, which focused on validation of the Belief in Good Luck Scale, I also included the Superstitious Beliefs Scale (Stanovich & West, 1998). I will not report results relating to the Superstitious Belief Scale in the present chapter.

[2]The I-PANAS-SF has five items for positive affect and five items for negative affect. The five positive affect items are: Determined, Attentive, Alert, Inspired, and Active. The five negative affect items are: Afraid, Nervous, Upset, Ashamed, and Hostile.

analysis[1] of the ratings, and found that lucky stories were related to the following: accomplishment, escape from negative consequences, important consequences, prolonged consequences, and luck.

Given the findings in Wagenaar & Keren (1988), I thought it should be possible to construct a Luck Composite that contained words corresponding to each of these dimensions. The items were delivered immediately after the PANAS items, and were presented in exactly the same format, where a word appeared on the scale and a participant was requested to "Indicate to what extent you feel this way right now, that is, at the present moment." The scale was a six-point scale from with the following responses: very slightly or not at all, a little, moderately, quite a bit, and extremely. The word items I used were: lucky, fortunate, relieved, and successful. Some of these items were more closely paired than others with the scaling dimensions of Wagenaar & Keren (1988). In particular, 'escape from negative consequences' seems quite tightly coupled with 'relieved'; 'important and prolonged consequences' seems less tightly coupled with 'fortunate'; and 'accomplishment' seems perhaps least tightly coupled with 'successful'. Of course, 'luck' and 'lucky' are the same. This Luck Composite was meant to reflect the significant dimensions in Wagenaar & Keren (1988), providing more than a single indicator for psychometric robustness. Additionally, these items also provide an opportunity for a factor analysis and follow-up to their work.

4.2.3 Counterfactual Priming Task

Participants then completed a counterfactual priming task. As mentioned above, this consisted of three parts. The first part of the counterfactual priming task was to write about a personally experienced event. The second part was to formulate counterfactuals that described how the event might have turned out differently. The third part was to rate those counterfactuals with regards to their likelihood of occurring and impact on the outcome of the event had they occurred. Note that in the descriptions below [CONDITION] indicate Lucky, Unlucky, Positive, or Negative, depending on the condition of a participant.

[1] See table Exhibit 1 on page 69 of their paper for a spatial representation of these.

4.2.3.1 Story Writing

Participants were introduced to the first part of the counterfactual priming task, writing about a memorable [CONDITION] event, with the following text.

> **A Memorable [CONDITION] Event**
>
> On the next page you will be asked to write a brief summary of a single [CONDITION] event that you personally experienced the last year. There are probably a number of events you could choose from. To help you select from many possible events that you could write about, please keep in mind the following: The [CONDITION] event doesn't have to be a completely life changing one, but you should consider it one of the more significant and important events that you experienced in the last year. The [CONDITION] event you choose should be one that you clearly remember having told someone close to you about. For example, you might have called a friend or a family member to share with them the [CONDITION] event. Or, you might have gone home later in the day to tell a flatmate or your family about it.

On the next page, participants were asked to enter their story by typing into a text box. A javascript counter button was provided so that participants could count the words they had written. The exact instructions read:

> Please write at least 50 words about a significant and important [CONDITION] event you experienced in the last year. This event should be one that you can clearly remember telling someone about after you experienced it. Perhaps include details such as: where you were; what you were doing; who you were with; where you were going; where you had been; who did what; what you were thinking.

I wanted the event participants chose to write about to be personally significant, and also vividly and accurately recalled. I chose the time period of one year to give a cue as to the level of personal significance the event should have had. Although a shorter time might have had better recall, a period such as the previous week might have indicated a level of significance less than I desired. I felt that a longer time period might be problematic because of degraded vividness or accuracy of recall. Past research has shown that memory of an event is improved when it is recounted to another individual (Neisser, Winograd, Bergman, Schreiber, Palmer & Weldon, 1996), so the instructions included a prompt to that effect. I include suggestions regarding the content to assist participants in structuring their writing. Because of the subsequent task in the manipulation, the generation of counterfactuals, it was important that participants recall some details about the event.

4.2.3.2 Counterfactual Generation

The next part of the counterfactual priming task elicited counterfactuals from participants. Participants were asked to formulate three counterfactuals according to the following instructions. The prompt concluded with either 'Better' or 'Worse' depending on a participant's condition. For Lucky and Positive conditions, it read 'Worse', whereas for Unlucky and Negative, it read 'Better'. Note that the instructions included both additive and subtractive examples of counterfactuals.

> **A Memorable [CONDITION] Event. . . How it might have been different**
>
> People often can think about ways in which a significant [CONDITION] event might have turned out worse (better) or much worse (better). A person might say or think: 'If _____ would have happened, then I would have had a much worse (better) outcome'. (OR) 'If _____ would NOT have happened, then I would have had a much worse (better) outcome'.
>
> On the next page you'll be asked to write 3 different ways in which the [CONDITION] event you just wrote about earlier might have turned out worse (better) or much worse (better). Each item in your list should complete either of the following phrases:
>
> - If _____ would have happened, the outcome would have been much worse (better). (OR)
> - If _____ would not have happened, the outcome would have been much worse (better).

On the subsequent page, participants were provided three text boxes with instructions that paralleled the introductory page. Participants could not proceed until they had entered text in each box. There was a prompt in each box that restated the two 'If' statements in the instructions.

4.2.3.3 Counterfactual Rating

The third part of the counterfactual priming task consisted of participants rating each of the three counterfactuals they generated in terms of the likelihood of a given counterfactual of happening, and the impact of the counterfactual on the outcome of the event had the counterfactual eventuated. The instructions for this rating exercise read as follows:

> **A Memorable [Condition] Event. . . How it might have been different**
>
> On the previous page, you described three different ways that your [Condition] event might have been worse (better). For each of your previous descriptions, please indicate how likely it was that this alternative might have occurred. Please also indicate how much of an impact this alternative would have had on the outcome.

Participants were then shown the counterfactuals entered on the previous page, one at a time. For each of the three counterfactuals, participants were asked two questions, one about the probability of the counterfactual happening: "How likely is it that the alternative you described above might have actually happened?". The response format for this item was a six-point scale with the following alternatives: Very Unlikely; Quite Unlikely; Unlikely; Likely; Quite Likely; Very Likely. The second question was about the impact of the counterfactual on the outcome of their story: "How big of an impact on the final outcome would the alternative you described above have had?". The response scale for this item was also a six-point scale, but with different response alternatives: Virtually no impact; A little impact; Some impact; Quite a lot of impact; A big impact; A really big impact.

4.2.4 Post-Manipulation Measures

Participants were asked to again complete the PANAS (20 items) and the Luck Composite Scale. I used responses from time 1 to provide a baseline for time 2 positive affect (PA), negative affect (NA) and lucky composite (LC). Thus, the variables are change scores, calculated as Time 2 - Time 1. I prefix "Δ_" to each to indicate the variable, scale or construct (e.g., Δ_PA = T2_PA - T1_PA).

4.2.5 Overconfidence Trivia Task

I asked for performance estimates prior to a set of 11 trivia questions, and then again after participants completed the trivia questions. The questions were designed to be difficult, so that the post-task estimates would test the limits of persistence of overconfidence across the conditions. Prior to the pre-task estimates, I instructed participants

Target	Time	Estimate/Measure	Variable Label
Participant Estimate of Own Performance	Pre-Task	Correct responses (%)	T1_Me_Est
		Lower bound, 90% confident	T1_Me_Low
		Upper bound, 90% confident	–
	Post-Task	Correct responses (%)	T2_Me_Est
		Lower bound, 90% confident	T2_Me_Low
		Upper bound, 90% confident	T2_Me_High
Participant Estimate of Fellow Student Average Performance	Pre-Task	Correct responses (%)	T1_Oth_Est
		Lower bound, 90% confident	T1_Oth_Low
		Upper bound, 90% confident	–
	Post-Task	Correct responses (%)	T2_Oth_Est
		Lower bound, 90% confident	T2_Oth_Low
		Upper bound, 90% confident	T2_Oth_High
Actual Performance	During Task	Participant, (% Correct)	Me_Actual
		All-participant average (% Correct)	Average_Other

Table 4.1: Variable Labels for Calculations of Three Overconfidence Types: Overestimation, Overplacement and Overprecision - From left to right columns list: the target of the measure; the time that the measure was collected; a description of the measure; the variable label.

that a random element was employed in the selection of the trivia questions from different difficulty levels. Thus, participants' estimates of performance could potentially be influenced by lucky feelings (or affect) regarding their ability, or by the chance selection of easy trivia questions, or both. I provide the calculations for overestimation, overplacement, and overprecision next. For ease of discussion, and to avoid confusion, explanations of calculations for the three types of overconfidence will use variable labels provided in Table 4.1. (The text of the instructions and questions is presented in sub-sections to follow.)

Overestimation Calculations

Overestimation is the difference between a participant's estimate of percentage correct and his or her actual percentage correct. Overestimation may occur prior to the trivia task (T1_OE), or after the trivia task (T2_OE). Pre-trivia overestimation is calculated as the difference between a participant's actual score (Me_Actual) and their estimate prior to the task (T1_Me_Est). Likewise, post-trivia overestimation is calculated as the difference between a participant's actual score (Me_Actual) and their estimate after the task (T2_Me_Est). Thus, Overestimation variables are calculated as:

Pre-trivia Overestimation: T1_OE = T1_Me_Est – Me_Actual

Post-trivia Overestimation: T2_OE = T2_Me_Est – Me_Actual

A positive value for pre-task overestimation (T1_OE) and post-task overestimation (T2_OE) indicates that a participant's estimate exceeded his or her actual performance. A negative value for pre-task overestimation (T1_OE) and post-task overestimation (T2_OE) indicates that a participant's actual performance exceeded his or her estimate of performance. In other words, overestimation has occurred when there are positive values for T1_OE and T2_OE. Underestimation has occurred when a value is negative.

Overplacement Calculations Overplacement is the difference between a participant's estimate of how well he or she will do relative to others. A direct measure of overplacement would ask participants how they expect to performance in a ranked fashion (e.g., top 10% percent, top 20% percent, etc). A less direct measure compares estimates and overestimates of participant's own performance and their estimates of fellow students (average) performance. I elected to use the later as it did not force a direct comparison, and therefore fewer demand characteristics relative to the former.

Having asked participants for estimates of their own and others' performance, there are two methods for calculating overplacement. One method uses only estimates of performance, whilst the other takes into account actual performance. Using only estimates of performance (the first method), pre-task overplacement (T1_OP) is calculated as the difference between a participant's pre-trivia performance estimates of others (T1_Oth_Est) and a participant's pre-trivia performance estimate of himself or herself (T1_Me_Est). Likewise, post-trivia overplacement is calculated as a participant's post-trivia performance estimates of others (T2_Oth_Est) and a participant's post-trivia performance estimate of himself or herself (T2_Me_Est). Thus, the Overplacement variables are calculated as:

Pre-trivia Overplacement: T1_OP = T1_Me_Est – T1_Oth_Est

Post-trivia Overplacement: T2_OP = T2_Me_Est – T2_Oth_Est

Similar to before, a negative value for pre-task overplacement (T1_OP) and post-task overplacement (T2_OP) indicates that a participant's performance estimates exceeded that same participant's estimates of the average performance of fellow students.

In other words, overplacement has occurred when there are positive values for T1_OP and T2_OP. Underplacement has occurred when a value is negative.

The second method to calculate overplacement differs from the first in that actual performance is taken into account. To 'adjust' for actual performance, I subtract the actual performance of a participant from that participant's estimate of his or her own performance, and I subtract the average performance of all participants from a given participant's estimate of the average performance of fellow students. Thus, the Pre-trivia Adjusted Overplacement (T1_OP_adj) and Post-trivia Adjusted Overplacement (T2_OP_adj) is calculated as:

$$\text{T1\_OP\_adj} = (\text{T1\_Me\_Est} - \text{Me\_Actual}) - (\text{T1\_Oth\_Est} - \text{Average\_Other})$$
$$\text{T2\_OP\_adj} = (\text{T2\_Me\_Est} - \text{Me\_Actual}) - (\text{T2\_Oth\_Est} - \text{Average\_Other})$$

Pre- and post-task overplacement take the same signs as explained previously, namely that a positive value for either any of the above overplacement variables indicates overplacement and a negative value indicates underplacement.

Overprecision Calculations Recall that an html coding error resulted in the loss of a subset of estimates, namely the pre-trivia upper range estimate for self (T1_Me_High) and the pre-trivia upper range estimate for others (T1_Oth_High) Thus I'm unable to calculate overprecision for the sample prior to the trivia task. However, I do have the data required to calculate overprecision after the trivia task. Overprecision, as mentioned before, can only be calculated on the sample, or a group with the sample, but not for a single participant (unless the participant were to complete confidence estimates for each item, which they did not do in this study).

The calculation for overprecision is a simple procedure. It is based on the percentage of subjects who correctly specify a range that includes the actual performance. If a participant specified he or she would answer between 10% and 50% correct with 90% certainty, and actually answers 20% correct, the participant was scored on a dichotomous variable as having included his or her actual performance in the range. The sum of that dichotomous variable then is divided by the total number of participants to yield the percentage of participants for whom their 90% confidence range included their actual performance. If the percentage of participants for whom their 90% confidence range included their actual performance is equal to 90%, then the sample as a whole is precise in their estimates. However, if the percentage of participants for whom their 90% confidence range included their actual performance is *less than* 90%, then the sample as a whole is *over*precise.

For the entire sample, the total number of participants whose actual performance fell within the specified 90% interval was 61. There were 154 participants, so the percentage of correctly precise participants in the sample was 61/154 = 40%. There were no treatment group differences in post-task overprecision estimates. Group sizes ranged from 37 to 39, and the number of participants in each group that included the group average in their 90% confidence interval ranged from 15 to 16. Thus the minimum percent ranged from 39% to 42%.

4.2.5.1 Pre-Trivia Performance Estimates

The instructions and questions for the pre-trivia estimates read as follows:

> **Trivia Time !**
>
> In the next task, you'll be asked some trivia questions. These questions are randomly chosen from a large database containing an equal number of hard, medium, and easy trivia questions. Because it is a random draw from the database, there isn't any guarantee of the number of easy, medium and hard questions that you'll get. Even so, please enter the percentage you think you'll answer correctly.
>
> - I think I'll answer about _____ % correct.
> - Please complete the following sentence by entering a number from 1 and 100 in each of the two boxes. With 90% certainty, I think I will get between _____ % correct and _____ % correct.
>
> Just like you, your fellow students who participate in this study will receive questions randomly chosen from the same large database containing equal numbers of easy, medium, and hard trivia questions. Thus, there is very little chance they will get the exact same set of trivia questions you get. Furthermore, even though everyone will get the same total number of questions, because it is a random draw, they may or may not get the same number of hard questions, medium questions, and easy questions in their set of questions.
>
> - Please rate how well you think your fellow students will do answering a randomly drawn set of trivia questions from the same large database. I think that on average, participants (my fellow students) will get about _____ % correct.

- Please complete the following sentence by entering a number from 1 and 100 in each of the two boxes. With 90% certainty, I think the average participant (my fellow students) will get between _____ % correct and _____ % correct.

4.2.5.2 Trivia Task

Trivia questions were presented one at a time with an open field to enter typewritten responses. The trivia questions were quite difficult, made all the more so with the open response format. The trivia questions, with answers in parentheses, were:

1. Who is the father of actress Gwyneth Paltrow? (A: Bruce Paltrow)
2. In what film did actress Mae West say the line: "When I'm good, I'm very good, but when I'm bad I'm better"? (A: *I'm No Angel*, 1933)
3. Who is credited with inventing the wristwatch in 1904? (A: Louis Cartier)
4. The psychoactive ingredient in marijuana is THC. What does THC stand for? (A: Delta-9-Tetrahydrocannabinol)
5. What chemical element has the atomic number five? (A: Boron)
6. What evolutionary biologist wrote: "'Creation science' has not entered the curriculum for a reason so simple and so basic that we often forget to mention it: because it is false."? (A: Stephen Jay Gould)
7. What two South American countries are land-locked? (A: Bolivia and Paraguay)
8. What is the capital city of Uganda? (A: Kampala)
9. What Pacific island mountain claims to be the wettest spot on Earth? (A: Maui)
10. Bechuanaland was the colonial name of what country? (A: Botswana)
11. In what year did Nigeria gain its independence from Great Britain? (A: 1960)

I was quite lenient when scoring the trivia responses. For example, a response of 'tetrahydrocannabin' and 'tetrahydroxycannabinol' for question four, was scored as correct, although a response of 'Tetrahydrochloride' was not. Responses in question seven that contained at least a single correct answer were scored as entirely correct. I dropped the final item because only a small number of responses it were not recorded by the javascript program. This may have been an area in recording or lack of response by participants. Thus, the highest score possible was 10.

Each participant was scored for the total correct. Of 154 participants, 105 answered none correct, 37 answered one correct, 10 answered two correct, and 2 answered 3 correct. The grand average correct for the entire sample was 4.09%[1].

4.2.5.3 Post-Trivia Performance Estimates

The instructions and questions for the pre-trivia estimates read as follows:

> **Trivia Time !**
>
> Now that you've seen all the questions, we'd like to ask you how you think you did.
>
> - I think I answered about _____ % correct.
> - Please complete the following sentence by entering a number from 1 and 100 in each of the two boxes. With 90% certainty, I think I will get between _____ % correct and _____ % correct.
>
> We want you to think about how your fellow students would have done answering exactly the same questions you just did.
>
> - Please rate how well you think your fellow students will do, if they answered exactly the same set of trivia questions you just did. I think that on average, participants (if they got the same questions I did) would get about _____ % correct.
> - Please complete the following sentence by entering a number from 1 and 100 in each of the two boxes. With 90% certainty, I think the average participant (my fellow students) will get between _____ % correct and _____ % correct.

4.3 Preliminary Analyses

In this section, I present descriptives for the variables and scales that are used throughout the remainder of the chapter. I also examine the stories and counterfactuals generated by participants, to determine the quality of those stories. This is required in order to establish confidence in the potential of the manipulation to generate an effect on lucky feelings, affect, and overconfidence. In relation to the counterfactuals, I tested for differences by condition in the locus of the counterfactuals (external or internal), and the additivity (additive or subtractive). Though this is not a core element to the thesis, it provides insight into the nature of counterfactuals across the four different conditions.

[1] Recall from Section 4.1.3 that for difficult tasks, there is a general tendency for people to overestimate and underplace their performances.

For ease of discussion later, Table 4.2 provides labels, descriptions and item content for constructs and variables used in the analyses below. Not including condition, counterfactual direction, and counterfactual potency, there were 55 variables used in the various analyses, and referring to each of these in a longer form (e.g., pre-task rating of positive affect item ‘alert’) is quite unwieldy. The shorter form (e.g., T1_PA_01) is more economical when used in conjunction with Table 4.2. As well, these items and constructs are related in the nomenclature system, facilitating the correspondence between a given item and the construct or scale to which it belongs. For example, the belief in personal good luck construct (PGL) is made up of five items, each of which suffix an incremental number to the construct name (i.e., PGL_01; PGL_02; . . . PGL_05). A glance over the model presented in Figure 4.8 will lend further insight to the usefulness of this nomenclature.

A variable label may contain up to three pieces of information. Reading from right to left, the first piece of information will be the item number. To the left of that position will be the construct abbreviation. And finally, if a variable was measured on multiple occasions, the label to the left again will begin with “T1”, “T2”, or “δ”, to indicate whether that item refers to the measurement at, respectively, time 1, time 2, or is time 2 - time 1 change score. When there is no item number in the rightmost position, then the label refers to the construct.

Data were analysed using SPSS 12.0 for Windows (SPSS Inc, Chicago, IL) and SmartPLS 2.0 (Ringle, Wende & Will, 2005). For SPSS-based analyses, individual items have been averaged to form a scale, and the bolded labels in Table 4.2 indicate a scale. For PLS-based analyses presented in Sections 4.6 and 4.7, individual items are used to form a latent construct, and the same bolded labels in Table 4.2 are indicative of a latent construct (rather than a scale).

4.3.1 Descriptives for Variables and Scales

Descriptives for survey scales and overconfidence variables are provided in Table 4.3. Cronbach’s α for all scales met or exceeded the 0.70 level, with the exception of lucky composite at pre-manipulation (T1_LC) , which was marginal, and after the manipulation shifted slightly upward. Negative affect had a strong positive skew (toward zero) of 2.02 prior to the manipulation (T1_NA), which diminished slightly to 1.42 after the manipulation (T2_NA). The means were both low at 1.38 and 1.53 for pre-

Label	Text/Description
UBL	**Universal Belief in Luck**
UBL_01	I believe in luck.
UBL_02	Luck plays an important part in everyone's life.
PGL	**Personal Good Luck**
PGL_01	I consistently have good luck.
PGL_02	Luck works in my favor.
PGL_03	I consider myself to be a lucky person.
PGL_04	I often feel it's my lucky day.
PGL_05	Even the things I can't control tend to go my way because I'm lucky.

Time 1 Label	Time 2 Label	T2-T1 Label	Text/Description
T1_PA	**T2_PA**	**Δ_PA**	**Positive Affect**
T1_PA_01	T2_PA_01	Δ_PA_01	Alert
T1_PA_02	T2_PA_02	Δ_PA_02	Inspired
T1_PA_03	T2_PA_03	Δ_PA_03	Determined
T1_PA_04	T2_PA_04	Δ_PA_04	Attentive
T1_PA_05	T2_PA_05	Δ_PA_05	Active
T1_NA	**T2_NA**	**Δ_NA**	**Negative Affect**
T1_NA_01	T2_NA_01	Δ_NA_01	Upset
T1_NA_02	T2_NA_02	Δ_NA_02	Hostile
T1_NA_03	T2_NA_03	Δ_NA_03	Ashamed
T1_NA_04	T2_NA_04	Δ_NA_04	Nervous
T1_NA_05	T2_NA_05	Δ_NA_05	Afraid
T1_LC	**T2_LC**	**Δ_LC**	**Lucky Composite**
T1_LC_01	T2_LC_01	Δ_LC_01	Lucky
T1_LC_02	T2_LC_02	Δ_LC_02	Fortunate
T1_LC_03	T2_LC_03	Δ_LC_03	Relieved
T1_LC_04	T2_LC_04	Δ_LC_04	Successful

Pre Trivia Label	Post Trivia Label	Post-Pre Label	Description
T1_OE	**T2_OE**	**Δ_OE**	**Overestimation**
T1_OP	**T2_OP**	**Δ_OP**	**Overplacement**
T1_OP_adj	**T2_OP_adj**	**Δ_OP_adj**	**OP, adjusted**

Table 4.2: Variable Labels and Content - Labels and content for variables used in the analyses in this chapter. Construct (scale) labels and descriptions for a given set of items are in bold. The first block lists the luck belief items used, providing item content and labels. The middle block contains positive affect, negative affect and lucky composite items, listing the word for each item and then labels corresponding to pre-manipulation (Time 1 Label), post manipulation (Time 2 Label) and pre - post difference (T2-T1 Label). The final block contains labels for measures of calculated overestimation, overplacement, and overplacement adjusted (OP, adjusted).

and post-manipulation respectively. This indicates that on average participants were not experiencing much negative affect at the time of the surveys. There was a slight positive skew of 0.40 for lucky composite after the manipulation (T2_LC). Otherwise these scales were quite normally distributed.

Looking still at the results presented in Table 4.3, reliabilities for the change score of positive affect (Δ_PA) and the change score of lucky composite (Δ_LC) degraded slightly as compared to the scales that comprise them (recall that Δ_PA = T2_PA – T1_PA; and Δ_LC = T2_LC – T1_LC). This may not be surprising given that there are four treatment conditions in the dataset and response patterns may have differed by treatment in terms of the difference scores. The relatively stronger α for the negative affect scales is likely a consequence of the tight clustering of responses—the change score for negative affect (Δ_NA) was very highly kurtotic for the entire sample at 6.86, indicating that there was little change from pre- to post-manipulation.

Mean values for the changes scores in positive affect, negative affect and lucky composite (respectively, Δ_PA, Δ_NA and Δ_LC) were all near zero and at most within the range of a single standard deviation. Recall that there are four groups aggregated in the dataset. I will present group comparisons momentarily.

Overestimation of own performance following the trivia task (Post-trivia Overestimation: T2_OE) had restricted variance, with 46% of participants accurately predicting they answered no trivia questions correctly. This reflects the high difficulty of the trivia questions, and thus the relative ease of accurately predicting one's performance. I expect that only in extreme cases of overestimation would a non-zero response occur on Post-trivia Overestimation (T2_OE). The frequency of correct estimates of performance after the trivia task (i.e., T2_OE=0) by group were: Lucky=42%; Unlucky=46%; Positive=51%; and Negative=44%. Given the relatively low performance across the sample, one might expect a floor-effect for overestimation. This however did not appear to be the case. In the same order as previously, the frequencies by condition of T2_OE<0 were: 26%, 20%, 13%, and 30%. So, while there was clearly a high modal response at zero for Post-trivia Overestimation (T2_OE), there may be enough variance for prediction using a non-parametric technique.

The means for overplacement and overplacement-adjusted-for-performance were virtually identical, and the minimum and maximum values were similar. They are correlated 0.91 for measures before the trivia task (i.e., T1_OP correlated with T1_OP_adj)

Scale Label	Mean	SD	Min	Max	Cronbach's α
UBL	3.70	1.24	1.00	6.00	0.73
PGL	3.21	0.96	1.00	6.00	0.85
T1_PA	2.96	0.73	1.40	4.60	0.74
T1_NA	1.38	0.57	1.00	3.60	0.81
T1_LC	2.45	0.79	1.00	4.25	0.69
T2_PA	2.71	0.81	1.00	4.80	0.81
T2_NA	1.53	0.65	1.00	3.60	0.82
T2_LC	2.18	0.85	1.00	4.25	0.80
Δ_PA	-0.26	0.55	-2.40	1.00	0.62
Δ_NA	0.15	0.52	-1.20	2.40	0.76
Δ_LC	-0.28	0.74	-2.50	2.50	0.65
T1_OE	54.90	18.57	-9.00	90.00	—
T1_OP	-5.97	15.40	-55.00	55.00	—
T1_OP_adj	-5.97	16.23	-65.91	49.09	—
T2_OE	0.06	7.41	-20.00	30.00	—
T2_OP	-20.21	16.75	-60.00	15.00	—
T2_OP_adj	-20.17	16.76	-55.91	9.09	—

Table 4.3: Descriptives for Scales and Overconfidence Variables - Reported are the mean, standard deviation, minimum, and maximum. Cronbach's α is reported for scales. See Tables 4.1 and 4.2 for item content and descriptions. The sample contained responses from 154 participants.

and 0.92 for measures following the trivia task (i.e., T2_OP correlated with T2_OP_adj). I will disregard the measures of overplacement not adjusted for actual performance (T1_OP; T2_OP) from here forward. There seems to be little difference between the un-adjusted and the adjusted measures and the adjusted measure more precisely reflects the conceptual aspects of overplacement.

In the following SPSS-based analyses, I took caution with scales involving negative affect after the manipulation, namely post-trivia negative affect (T2_NA) and the change score of negative affect (Δ_NA). Otherwise I consider the scale and variable properties sufficient for ANOVA and basic regression.

Source	Mean	SD	Min	Max
Story	605	320	214	1901
CF 1	100	37	16	273
CF 2	104	43	8	272
CF 3	104	46	9	301
Total	914	373	316	2422

Table 4.4: Descriptives for Character Counts of Stories and Counterfactuals - Reported are the mean, standard deviation, minimum, and maximum for character counts of the stories and counterfactuals (CF) entered in sequence by participants. The total is the sum of the story, and CF 1, CF 2, and CF 3 calculated for each participant. The average characters per story-words over the entire dataset was 5.15.

4.3.2 Story and Counterfactual Content

Two participants entered text indicating that they could not recall an event of the nature requested, one lucky and one unlucky. I have removed them from any analyses involving group differences or counterfactuals as predictors. I provide the character count of stories and counterfactuals in Table 4.4. Closer inspection of the low character count entries provided some confidence that extremely low entries did not reflect low levels of engagement with the task. For example, one person recounted a story about meeting a schoolfriend from younger days and going for a scenic walk on a sunny day. The participant later went for drinks with the friend and her husband, and had an “extraordinary day”. The counterfactuals, although short, were reasonable: “If I hadn’t recognised my friend”; “If it had been raining”; “If her husband hadn’t been so pleasant”.

Participants’ stories varied widely in content and personal relevance. Some stories revealed very serious events and consequences such as the divorce of parents or death of a loved one. These types of stories seemed concentrated in the negative condition. Other stories were more light-hearted, such as happy accidents like meeting a friend above. There were a number of stories of memorable social events, such as birthday parties, in the positive condition. Finally, reflective of the participants’ student status, many stories were focused on entrance exams, course assessments, finding flatmates, nights out or other concerns typical of a student. These stories seemed to cut across conditions.

I have already presented a lucky story on page 127. To provide additional insight into the stories, below are unedited stories and counterfactuals from the three other conditions.

Unlucky Condition **[Story]** The unlucky event happened on a morning, I went to work as usual. But the bus I waited for was late for about half a hour. Generally I arrived at office in 15 mins advance, so that day I was 15 mins late. Unfortunately, I found my boss and other managers standing in the front of company door. Everyone saw me. It was really a bad impression to be late confront so many people. It turns out that there was an ISO inspection that day. They all waited for the inspectors. I was unlucky late on an key day.

[CF1] If an advance notice about the inspection would have been informed, then I would have taken a taxi and would not be late.

[CF2] If the bus I took would not come late, then I would not be late.

[CF3] If I would have talked to my colleague and remembered the inspection date, then I would not be late on that day.

Positive Condition **[Story]** I got a distinction mark on my HR performance management essay last year. I considered it as a positive event was because that was my first distinction essay I got in the Sydney University. As I am well informed, it is farly difficult to get good marks in an English speaking country when my mother language is not English, not to mention this is my first oversea study experience. I spent quite a few weeks on the essay and I finally had my return.

[CF1] I didnt spend my time and effort on it

[CF2] My lecturer didnt give us lot of information on how to repare the essay.

[CF3] If Sydney university didnt have quite much research resource for us to study.

Negative Condition **[Story]** I was at home one night in July watching TV with my flatmate in our apartment when my parents called to tell me that there was a chance my father might have prostate cancer. I talked with them for about half an hour about the course of action he would be taking and when we would get results. At the time I was thinking that what they were telling me wasn't the full story and that things were worse than they were making things out to be.

[CF1] If my father had have been checked earlier, then i would have had a much better outcome.

[CF2] If my father's family did not have a history of prostate cancer, then I would have had a much better outcome.

[CF3] If the results had not come back positive, then I would have had a much better outcome.

I coded all counterfactuals for external/internal orientation, consistent with Section 4.1.1.1. Some counterfactuals (20 out of 456) were ambiguous, and I coded these as missing values. I summed the counts of external counterfactuals over the three counterfactuals for each participant. I expected differences between the two groups in the luck conditions (i.e., Lucky and Unlucky) to differ from the two groups in the non-luck conditions (i.e., Positive and Negative) on the count of external counterfactuals. To test for this, I ran a χ^2 analysis of the sum of externally oriented counterfactuals for the four conditions and for two combined luck groups versus the two combined non-luck groups. There was no statistically significant difference for the four conditions ($\chi^2(9) = 8.626$, $p = .473$). There was also no statistically significant difference for the two combined luck groups versus the two combined non-luck groups ($\chi^2(3) = 2.465$, $p = .482$). The counts are presented in the first block of Table 4.5

I also coded all counterfactuals for additive or subtractive orientation. Some counterfactuals (16 out of 456) were ambiguous, and as before I coded these as missing values. I summed the counts of additive counterfactuals over the three counterfactuals for each participant. I had no a priori expectations regarding group differences. Counts by group showed a strong relationship of additive with upward counterfactual conditions of Unlucky and Negative, so I combined these groups together. These counts are presented in the second block of Table 4.5. For additively oriented counterfactuals both by condition and by grouped conditions, there were statistically significant differences in the counts (respectively, $\chi^2(9) = 28.65$, $p < .001$ and $\chi^2(3) = 26.18$, $p < .001$).

Counterfactual potency, discussed in Section 4.1.1.2, is computed as the product of the likelihood and impact of a given counterfactual. With three counterfactuals, I can calculate a few variants of the counterfactual potency (CP) measure to get some insight into the participant experience of counterfactual generation. Table 4.6 provides descriptives for different variants of the CP measure: the CP measures in sequence, and the maximum, median, minimum and mean of the three CP measures.

As can be seen in that table, there is little downward trend from CP1 to CP3. I anticipated that counterfactual potency might decrease with each counterfactual if the more obvious and impactful counterfactuals were recalled first. Looking at the maximum, median, and minimum, it is clear that there were differences, on average, within subjects across the three CP ratings.

I note that the mean of the three CP ratings is quite close to CP1. I had initially thought that I might be forced to use only the first counterfactual because of diminish-

Groups	Count of External Counterfactuals 0	1	2	3	Total
Lucky	3	9	11	13	36
Unlucky	6	11	11	10	38
Positive	5	9	11	13	38
Negative	10	12	5	10	37
—	–	–	–	–	–
Lucky+Unlucky	15	21	16	23	75
PosItive+Negative	9	20	22	23	74
—	–	–	–	–	–
Total	24	41	38	46	149

Groups	Count of Additive Counterfactuals 0	1	2	3	Total
Lucky	9	17	6	4	36
Positive	9	17	8	4	38
Unlucky	1	8	12	17	38
Negative	5	9	10	13	37
—	–	–	–	–	–
Lucky+Positive	18	34	14	8	74
Unlucky+Negative	6	17	22	30	75
—	–	–	–	–	–
Total	24	51	36	38	149

Table 4.5: Counts of Externally and Additively Oriented Counterfactuals by Groups - The first block presents the count of externally oriented counterfactuals by the four treatment groups and by combinations of groups that either did or did not have a luck element (i.e., Lucky+Unlucky versus Positive+Negative). The second block presents the count of additively oriented counterfactuals by the four treatment groups and by direction of counterfactual (i.e., Downward = Lucky+Positive; Upward = Unlucky+Negative). Note that the order of variables in the first column is not identical for the first and second blocks.

CP Variant	Mean	SD	Min	Max
CP 1	14.49	6.11	3	25
CP 2	14.26	5.44	2	25
CP 3	12.72	5.63	3	25
CP Maximum	18.07	4.47	4	25
CP Median	13.99	4.74	4	25
CP Minimum	9.42	4.51	2	20
CP Mean	13.83	3.89	4	21.67

Table 4.6: Descriptives for Counterfactual Potency (CP) Measures - Reported are the mean, standard deviation, minimum, and maximum for variants of the CP measure.

ing CP strength or counterfactual quality[1]. Histograms reveal that CP1, CP2 and CP3 did not have a very smooth distribution. This is not surprising given the Likert response format of the ratings for likelihood and impact[2]. Because of the near equivalence of CP1 and CP_mean, and the more normal distribution of CP_mean, I restrict analyses to CP_mean.

4.4 The Lucky Feelings Composite Measure

The measure for lucky feelings used throughout the analyses in this chapter represents a potential means to examine differences between lucky-expectancy and lucky-gratitude with respect to predictors and the overconfidence dependent variables. Although the word 'lucky' may mean either lucky-fortunate or lucky-expectancy, the word 'fortunate' ostensibly would excluded lucky-expectancy. The PLS models that I will describe next all contain this lucky composite, so it is important to understand how the elements of the lucky composite related to one another, as well as to other variables in the study.

Recall that the lucky composite measure used four words that corresponded to the dimensions of lucky stories from Wagenaar & Keren (1988). Those words were lucky, fortunate, relieved, and successful. They factored together into a single factor and had

[1] There is some precedence to use only the first counterfactual generated (Markman, Gavanski, Sherman & McMullen, 1993, p. 97).

[2] Possible ratings for the first six variants in Table 4.6 are restricted to one of 14 values in the matrix formed by arrays 1x1 . . . 1x5 and 5x1 . . . 5x5.

acceptable internal consistency with a Cronbach's α of 0.69, 0.80, and 0.67 respectively for pre-manipulation, post-manipulation, and change score measures.

Table 4.7 presents a correlation matrix for the four lucky composite items, along with select other variables from the study. The first block provides correlations for measures taken prior to the experimental manipulation, the second block provides correlations for measures taken after, and the third block reports correlations for change scores. (Note that GBL and PGL were measured only once, at the beginning of the study.) The correlations of the 'lucky' and 'fortunate' items with other variables do not differ substantially. For example, in the first block of Table 4.7, correlations of 'lucky' and 'fortunate' with positive affect are 0.16 and 0.23 respectively. In the second block, 'lucky' and 'fortunate' correlate with positive affect 0.26 and 0.30 respectively. Pre-manipulation measures of 'lucky' and 'fortunate' correlate with PGL at 0.36 and 0.33, and post-manipulation measures of 'lucky' and 'fortunate' correlate with PGL at 0.39 and 0.31 respectively. Note also that 'lucky' and 'fortunate' are correlated highly with each other at both pre- and post-manipulation, and only moderately so for the change score. The two items appear to be similar in the way they relate to other variables, but they are not unitary.

The 'lucky' and 'fortunate' items clearly act similarly within affect measures and luck-related measures. But perhaps lucky composite items differed in their response to the experimental manipulation? To test for this I conducted a one-way ANOVA using condition as the between-subjects factor. I tested four different response variables. The first two were the post-manipulation ratings for 'lucky' and 'fortunate'. There was no statistically significant difference in means for either luck item (respectively, F (3, 150) = 1.239, $p = .30$; = 0.592, $p = .621$). The second two response variables were the change scores for 'lucky' and 'fortunate'. Again, there was no statistically significant difference in means for either luck item (respectively, F (3, 150) = 2.408, $p = .07$; = 2.366, $p = .07$).

It appears that the 'lucky' and 'fortunate' items, as used in this study, reflect the construct they measure in an almost equivalent manner. That is to say, there are no substantial differences between the items in terms of predictors (i.e., GBL, PGL, Positive Affect (PA), Negative Affect (NA), and other Lucky Composite (LC) items). Nor is there a difference in the response of these two items to the overall experimental conditions.

[Pre-Manipulation]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**GBL**	**PGL**
(1) T1_Lucky	1.00	0.51	0.32	0.38	0.16	0.20	0.78	0.27	0.36
(2) T1_Fortunate	0.51	1.00	0.19	0.46	0.23	0.20	0.76	–	0.33
(3) T1_Relieved	0.32	0.19	1.00	0.27	0.21	0.20	0.61	–	0.20
(4) T1_Successful	0.38	0.46	0.27	1.00	0.37	0.42	0.73	–	0.26
(5) T1_PA	0.16	0.23	0.21	0.37	1.00	0.59	0.34	–	–
(6) T1_NA	0.20	0.20	0.20	0.42	0.59	1.00	0.35	–	–
(7) T1_LC	0.78	0.76	0.61	0.73	0.34	0.35	1.00	–	0.40
[Post-Manipulation]	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**GBL**	**PGL**
(8) T2_Lucky	1.00	0.61	0.46	0.45	0.26	–	0.79	0.28	0.39
(9) T2_Fortunate	0.61	1.00	0.44	0.63	0.30	–	0.86	0.19	0.31
(10) T2_Relieved	0.46	0.44	1.00	0.4	0.32	–	0.72	–	–
(11) T2_Successful	0.45	0.63	0.4	1.00	0.57	–	0.79	–	0.21
(12) T2_PA	0.26	0.30	0.32	0.57	1.00	–	0.46	–	–
(13) T2_NA	–	–	–	–	–	1.00	–	–	–
(14) T2_LC	0.79	0.86	0.72	0.79	0.46	–	1.00	0.17	0.33
[Change Scores]	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**	**GBL**	**PGL**
(15) Δ_Lucky	1.00	0.34	0.30	0.38	0.19	–	0.72	–	–
(16) Δ_Fortunate	0.34	1.00	0.17	0.42	0.23	–	0.71	–	–
(17) Δ_Relieved	0.30	0.17	1.00	0.36	–	–	0.65	–	–
(18) Δ_Successful	0.38	0.42	0.36	1.00	0.26	–	0.74	–	–
(19) Δ_PA	0.19	0.23	–	0.26	1.00	-0.18	0.29	–	–
(20) Δ_NA	–	–	–	–	-0.18	1.00	–	0.18	–
(21) Δ_LC	0.72	0.71	0.65	0.74	0.29	–	1.00	–	–

Table 4.7: Lucky Feelings Composite Measure - Item Correlations - Correlations for which $p \geq .05$ level have been omitted, and are indicated by "–". The top block corresponds to pre-manipulation collection, the middle block to post-manipulation, and the final block to change scores. Scales for positive affect (PA) and negative affect (NA), and the lucky composite (LC) scale are provided within each block. Correlations with GBL and PGL luck belief subscales are provided to the right of each block. (All scales are formed using the average of item responses.) Note that lucky and fortunate items do not substantially differ in their correlations with other variables, especially the lucky composite scales.

The lucky composite will be comprised of all four items in the analyses and modelling to follow.

4.5 Treatment Group Differences

I first tested for treatment group differences on the ultimate dependent variables of overconfidence. There are a total of four: overestimation prior to the trivia task (T1_OE), and overestimation after the trivia task (T2_OE); and overplacement prior to the trivia task (T1_OP_Adj), and overplacement after the trivia task (T2_OP_adj). I conducted a one-way ANOVA for mean differences on each of these overconfidence measures, using condition as the between-subjects factor. In no case was there a statistically significant difference (in the same order as just listed, F (3, 150) = 0.667, $p = .57$; = 0.631, $p = .60$; = 1.636, $p = .18$; = .705, $p = .55$).

I then conducted an ANOVA test on the means of change scores for positive affect (Δ_PA), change scores for negative affect (Δ_NA), and change scores for lucky composite (Δ_LC), again using condition as the between-subjects factor. In no case was there a statistically significant difference (in the same order as just listed, F (3, 150) = 1.028, $p = .38$; = 0.870, $p = .46$; = 2.070, $p = .11$). As would be expected, similar results were obtained using the post-manipulation measure of positive affect (T2_PA), post-manipulation measure of negative affect (T2_NA), and post-manipulation measure of lucky composite (T2_LC) [in the same order as just listed, F (3, 150) = 1.160, $p = .33$; = 1.472, $p = .23$; = 0.569, $p = .67$].

The four conditions comprise a 2x2 matrix of counterfactual direction (lucky/positive versus unlucky/negative) and luck content of story (lucky/unlucky versus negative/positive). This design allows for a mixed-design ANOVA test. A significant interaction in this test would indicate whether one of the conditions in the graph presented in Figure 4.3 differed significantly from the others. I conducted a 2x2 mixed design ANOVA based on counterfactual direction and luck content, as just described), with change score for negative affect (Δ_NA) as the dependent variable in the first test and change score for lucky composite (Δ_LC) in the second test. The interactions were not statistically significant (respectively, F (1, 150) = 1.233, $p = .27$; = 0.281, $p = .60$). There was however a main effect for counterfactual direction on change score for lucky composite (Δ_LC; F (1, 153) = 5.290, $p = .023$).

To investigate this further, I graphed the group means of change score for lucky composite (Δ_LC), and additionally change score for positive affect (Δ_PA) and change score for negative affect (Δ_NA). Although there were no significant overall group differences for any of these variables, the means for each trended together for the Lucky and Positive groups in a seemingly distinct manner compared to the Unlucky and Negative groups. Visual inspection of the graphs in Figure 4.3, which plot the four groups' means for each of these three variables is illustrative (means for each condition are provided in the plots).

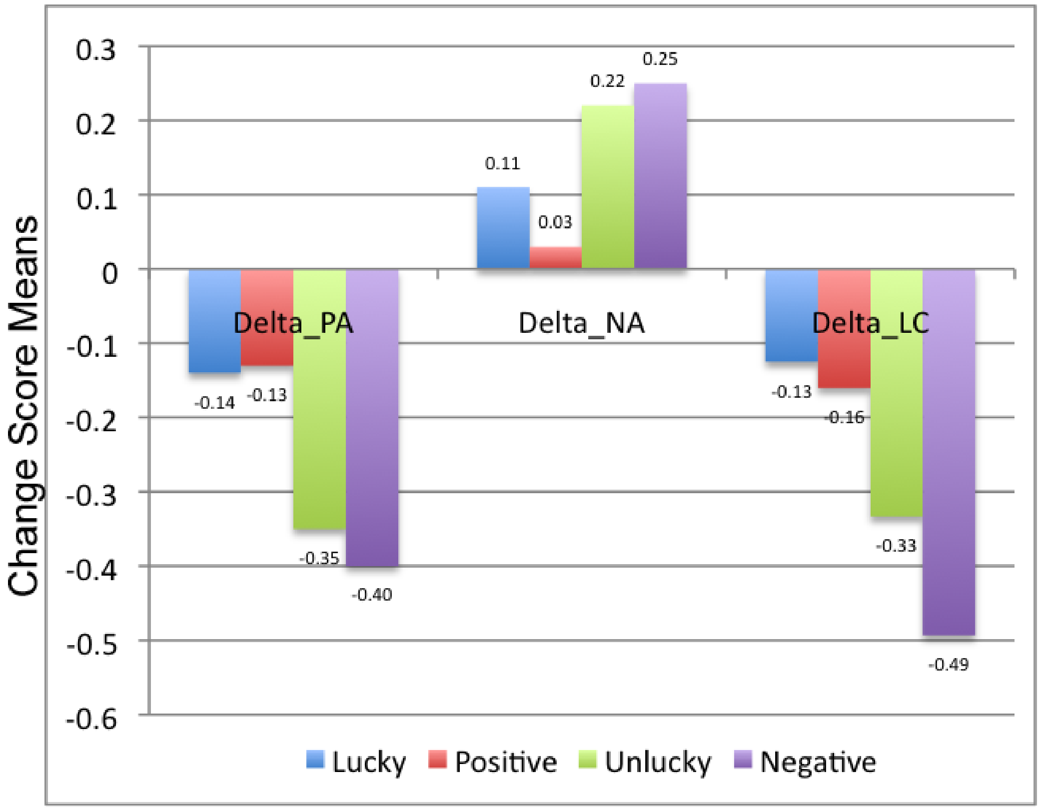

Figure 4.3: Change Score Means (Δ_PA, Δ_NA, Δ_LC), by Experimental Condition - Means for each group are provided for change in positive affect (Δ_PA), change in negative affect (Δ_NA), and change in lucky composite (Δ_LC). Each change score is calculated as Time 2 variable - Time 1 variable. Groups are ordered from left to right as per the legend, for each variable. Note the similar values for Lucky and Positive, and the similar values for Unlucky and Negative.

Groups that result from collapsing across Lucky and Positive and collapsing across Unlucky and Negative are equivalent to groups by counterfactual direction (downward and upward, respectively). This is most clearly warranted for change in positive affect (Δ_PA), the leftmost cluster in Figure 4.3. Though the trend is apparent, there is a less convincing case for change in negative affect (Δ_NA) and change in lucky composite (Δ_LC).

A one-way ANOVA comparing the combination of the two groups that generated downward counterfactuals (i.e., Lucky and Positive) with the combination of the two groups that generated upward counterfactuals (i.e., Unlucky and Negative) yielded significant differences for change in positive affect [Δ_PA; $F(1, 153) = 7.84$, $p = .006$], change in negative affect [Δ_NA; $F(1, 153) = 3.90$, $p = .050$], and change in lucky composite [Δ_LC; $F(1, 153) = 5.78$, $p = .023$]. Group means are reported in Table 4.8, and those for individual conditions can be seen in Figure 4.3. It is informative that direction of counterfactual was more instrumental in changing positive affect, negative affect and lucky feelings compared to individual conditions only, and will be explored more fully in Section 4.6.

I call attention to the direction and magnitudes of the shifts reported in Table 4.8. For change in positive affect (Δ_PA) and change in lucky composite (Δ_LC), the downward counterfactual group did not, on average, result in an *increase* in positive affect and lucky feelings. Rather, it resulted in *less of a reduction* in positive affect and lucky feelings, relative to the upward counterfactual group. One (optimistic) explanation for this is that some element or combination of elements of the Lucky Story, Positive Story or Downward Counterfactual had a buffering effect against what was an otherwise positive-affect reducing experience of the experiment. The group means for change in negative affect (Δ_NA) support this explanation — those in the Unlucky and Negative Conditions had, on average, a shift toward greater negative affect.

Most subjects could reasonably be expected to find the experiment tedious and boring which could have the net effect of altering affect and lucky feelings consistent with this interpretation. However, although this is a plausible explanation, there are other alternative explanations that have graver consequences for the conclusions that may be taken from this study. I will proceed with further analyses mindful of this concern.

Although based on null-findings for treatment group differences, my interim conclusions were that it is the direction of counterfactual that alters positive and negative

Group	**Δ_PA**	**Δ_NA**	**Δ_LC**
Downward (Lucky+Positive)	-0.14 *(0.58)*	0.07 *(0.46)*	-0.14 *(0.84)*
Upward (Unlucky+Negative)	-0.38 *(0.48)*	0.23 *(0.56)*	-0.41 *(0.59)*

Table 4.8: Change Score Means (Δ_PA, Δ_NA, Δ_LC), by Counterfactual Direction - Means are provided, with standard deviations in parentheses, for change in positive affect (Δ_PA), change in negative affect (Δ_NA) and change in lucky composite (Δ_LC). The group differences for each of the three variables are statistically significant at the $p \leq .05$ level.

affect, and lucky feelings. The conditions of lucky or positive story appeared to be undifferentiated in the direction and degree to which changes in positive affect resulted. The pattern was similar, but not as stark, for negative affect and for lucky composite.

This demonstrates that it is not the concept of lucky versus unlucky priming that activates affect or lucky feelings. There were some differences between groups, so perhaps the concept of luck primes individuals to some extent, but the larger trend shows that where there is a counterfactual involved, positive and lucky cognitions have similar outcomes, and that negative and unlucky cognitions have similar outcomes.

The result is of practical significance because it indicates that collapsing across the lucky and positive condition, and also across the unlucky and negative condition, is warranted for further analyses. So, from this point forward, I will no longer refer to the original conditions. Instead I will focus on counterfactual direction (upward or downward), which simplifies analyses and discussion considerably.

4.6 The Influence of Counterfactual Thinking and Affect on Lucky Feelings

To what extent does counterfactual potency influence lucky feelings? And does counterfactual potency explain more variance in lucky feelings than counterfactual direction? What role do positive and negative affect play?

I address these questions in this section, exploring both counterfactual thinking and affect as possible origins of lucky feelings. I begin with some regression-based analyses that look at the differences between counterfactual direction and counterfactual potency in explaining lucky feelings. I then specify a PLS model to further examine the interrelationships among counterfactual potency, affect and lucky feelings.

As an initial test for the interactive effect of counterfactual direction and counterfactual potency, I multiplied of the mean of three counterfactual potency measures by -1 for the Unlucky and Negative conditions, to yield a 'Valenced-CP_mean' (Val_CP_mean). I then tested the correlation of this with change in lucky composite (Δ_LC). There was a significant correlation of 0.172 ($p = .034$). So, at first pass it appears that counterfactual potency has some explanatory power of lucky feelings. To test whether this holds when other variables are included as predictors, I ran a hierarchical regression predicting change in lucky composite (Δ_LC) with direction of counterfactual (Lucky_Positive), and with change in positive affect (Δ_PA) and change in negative affect (Δ_NA).

As can be seen in Table 4.9, counterfactual potency explains no significant variance above and beyond that small amount explained by direction of counterfactual (Lucky_Positive), and affect explains a moderate portion of the variance in the change in lucky composite (Δ_LC). The (univariate) β of 0.168 for counterfactual direction (Lucky_Positive) is nearly equivalent to the 0.172 correlation between the valenced counterfactual potency mean (Val_CP_mean) and the change in lucky composite (Δ_LC). This indicates that counterfactual direction and counterfactual potency are predictive of almost exclusively overlapping variance, a conclusion supported by the correlation of 0.960 ($p = .000$) between direction of counterfactual (Lucky_Positive) and valenced counterfactual potency mean (Val_CP_mean).

Although the model with both valenced counterfactual potency mean (Val_CP_mean) and counterfactual direction (Lucky_Positive) was not significant, a commonality coefficients assessment can clarify the extent to which variance explained is overlapping. As expected, the direction of counterfactual predicts no variance unique from the valenced counterfactual potency. This is because the valenced counterfactual potency variable contains all the information inherent to direction of counterfactual. More interesting though, is that only 32% of the variance explained by valenced counterfactual potency mean (Val_CP_mean) is unique from counterfactual direction (Lucky_Positive). This unique amount then would constitute only 0.029 * 0.32 = 0.93% of the total variance in change in lucky composite (Δ_LC). To clarify, the (statistically non-significant) amount of variance in change in lucky composite (Δ_LC) explained uniquely by counterfactual potency amounts to less than 1%.

Step	Variables Entered	Δ_LC		
		β	p	adj. R^2
1	Lucky_Positive	0.168	0.039	2.2%
2	Lucky_Positive	0.056	0.854	
	Val_CP_mean	0.117	0.699	1.6%
3	Lucky_Positive	-0.060	0.829	
	Val_CP_mean	0.134	0.631	
	Δ_PA	0.300	0.000	
	Δ_NA	-0.243	0.002	17.0%

Table 4.9: Hierarchical Regression Predicting LC Change Score (Δ_LC) - The direction of counterfactual is entered in step 1 as Lucky_Positive. In step 2, the valenced counterfactual potency (mean) is entered as Val_CP_mean. In the final step, the change in positive and negative affect are entered as Δ_PA and Δ_NA respectively.

I note that in Step 3 of Table 4.9 the change in positive affect (Δ_PA) and change in negative affect (Δ_NA) both are statistically significant, in the expected directions (i.e., Higher levels of Δ_PA are associated with higher levels of Δ_LC), and together incrementally explain a large amount of variance with a ΔR^2 of 16%.

These findings call into question theory that directs our attention to the proximity of the hypothetical world to the real world as a practical predictor of the *degree* to which a person will experience lucky feelings. Instead, it appears that *direction alone* is predictive, and even direction pales in comparison to positive and negative affect.

This is an important finding that merits further investigation. To my knowledge, no studies have been conducted that look at the impact of counterfactual potency on lucky feelings. Petrocelli et al. (2011) looked at the impact of counterfactual potency on regret, causation and responsibility. A few studies have looked at the impact of closeness and lucky feelings or attractiveness and lucky feelings, but not the combination of closeness and attractiveness. To summarise the findings of this section: 1) counterfactual direction has a weak but statistically significant relationship with the change in lucky feelings, and counterfactual potency explains virtually no additional variance; and 2) Changes in positive and negative affect were associated with change in lucky feelings.

4.6.1 PLS Model of Counterfactual Direction, Affect and Lucky Composite

I now use a PLS analysis to further investigate the influence of counterfactual direction and affect on lucky feelings. Below I specify and assess a model proposing interrelationships among the variables I have been discussing. I proceed through the usual steps of measurement model assessment and structural model assessment, and conclude with a brief discussion.

Figure 4.4 presents the proposed model. There are four constructs in the model. The only exogenous construct is counterfactual direction. It predicts the change in positive affect (Δ_PA), the change in negative affect (Δ_NA), and the change in the lucky composite construct (Δ_LC). In turn each of the affect constructs predict Δ_LC. Recall that item content for each of the indicators is provided in Table 4.2.

The model situates affect as a mediator of counterfactual direction, allowing for the direct prediction of counterfactual direction of the lucky composite construct. An alternative model using counterfactual potency (instead of counterfactual direction) generated effectively equivalent results in all analyses below, as would be expected from the regression results in Table 4.9. However, to use counterfactual potency in the model seems misleading given the clearly predominant predictor of lucky feelings is counterfactual direction and not potency. I reiterate that counterfactual direction (upward or downward) is equivalent to collapsed conditions of unlucky and negative (upward counterfactuals) and lucky and positive (downward counterfactuals).

4.6.1.1 Measurement Model Assessment

Figure 4.5 presents the measurement model. The relationship between CF_Dir (counterfactual direction) and Δ_LC (change in lucky composite) was not statistically significant when the pathways from Δ_PA (change in positive affect) and Δ_NA (change in negative affect) were included.

The first step in the measurement model assessment is to verify the unidimensionality of the items for each construct. There is only a single indicator for counterfactual direction, and both positive and negative affect have been validated as a block in Thompson (2007). Change in lucky feelings (Δ_LC) has not yet been tested for unidi-

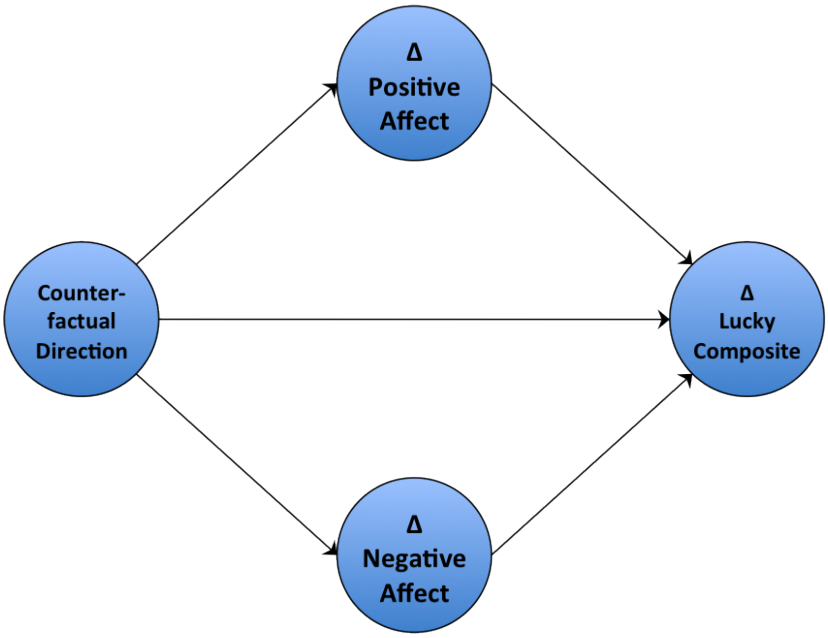

Figure 4.4: Full Model: Counterfactual Direction, Affect, Lucky Composite - A model for exploring counterfactual direction, affect and lucky composite. Δ_PA is the change in Positive Affect. Δ_NA is the change in Negative Affect. Δ_LC is the change in Lucky Composite. Each change score is calculated by subtracting Time 2 for an indicator from Time 1 for that same indicator.

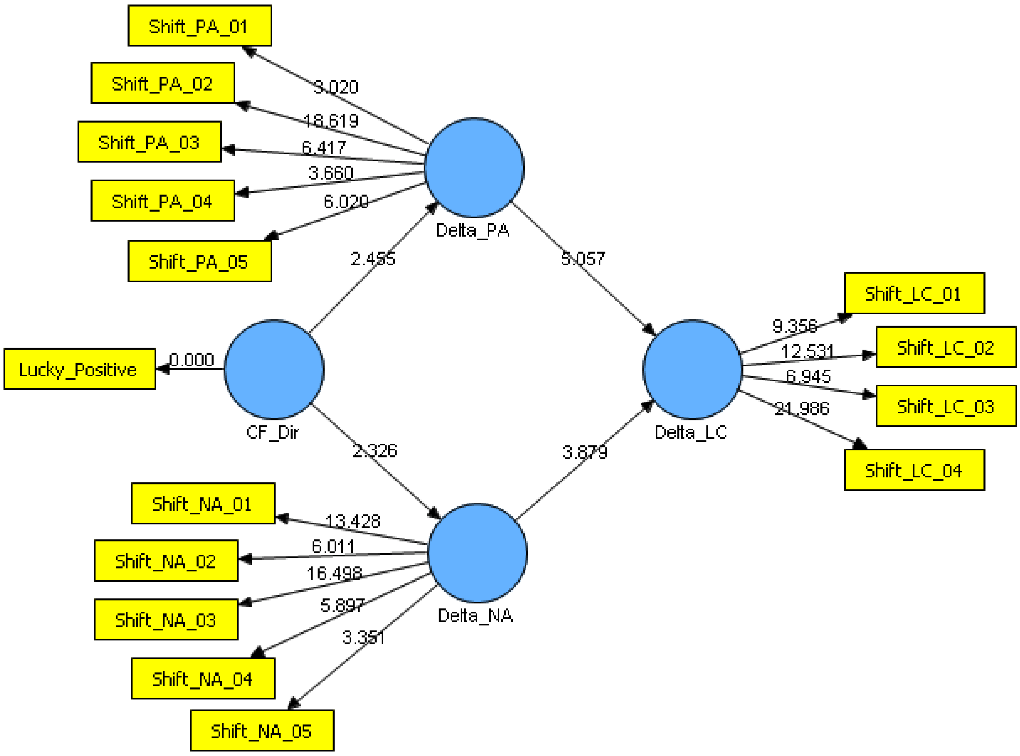

Figure 4.5: PLS Measurement Model of Counterfactual Direction, PA, NA, and LC - Bootstrap t-values (500 resamples) for a proposed PLS model of Counterfactual Direction (CF_Dir), change in positive affect (Delta_PA), change in negative affect (Delta_NA), and change in lucky feelings (Delta_LC). All paths and loadings were statistically significant ($p < .01$), except the originally specified path from CF_Dir to Δ_LC which has been removed. The t-value for that path (when the two affect constructs are present in the model was 0.947.

mensionality, but given its origins[1] it would be surprising if it were not. An exploratory factor analysis (principal axis factoring with direct oblimin rotation) in SPSS extracted only a single factor for the four-item block that makes up Δ_LC[2], with respectively, KMO and Bartlett's test results of 0.693 and $\chi^2 = 84.498$ ($df = 6$, $p = .000$). The Cronbach's α for the four item scale was 0.67. Dillon-Goldstein's ρ_c was 0.80 indicating that loadings of the indicators was not equivalent in the PLS calculation of the construct score.

All items in the model had statistically significant loadings. Table 4.10 provides the other metrics used in the measurement model assessment: Composite reliabilities (ρ_c) for each block of items, loadings and cross-loadings for the all items in the model, AVE's and latent variable to latent variable squared correlations.

The composite reliabilities surpassed the recommended level of 0.70. However, not all loadings exceeded the recommended threshold of 0.707. In particular, there was at least one item in each block with low values (i.e., Δ_LC_03, Δ_PA_01 and Δ_PA_04, and Δ_NA_05). On the other hand though, the cross-loadings were without exception below 0.50, with only Δ_LC_03 exceeding the more stringent level of 0.30 by a clear margin.

Change in positive affect, Δ_PA, had a low AVE value, and both change in negative affect, Δ_NA, and change in lucky composite, Δ_LC, had AVE's that exactly met the minimum value of 0.50. The Fornell-Larcker table did not identify any problematic failures of discriminant validity. In all cases the square root of AVE easily exceeds the latent variable correlations.

Although not an exemplary measurement model, the failings are limited to the ability of some items to reflect the latent construct. As such, those items may be thought of as clutter to the model. So long as the remaining items can be assumed to measure their construct well, these cluttering items are fairly innocuous. Items do not cross-load strongly onto other constructs and are probably not of sufficiently poor quality to otherwise threaten the structural model. This is indicated by the AVE's, the statistically significant paths between constructs, and as we shall see the R^2 values.

[1]Recall that the four items were mapped to a single dimension emerging from a discriminant analysis in Wagenaar & Keren (1988)

[2]For T1_LC and T2_LC, the factor analytic results were similar, and the for T1_LC and T2_LC was 0.69 and 0.80 respectively. These results indicate that the four item scale is unidimensional and moderately reliable.

	CF_Dir	**Δ_LC**	**Δ_PA**	**Δ_NA**
ρ_c	1.00	0.80	0.75	0.83
Lucky_Positive	**1.00**	0.15	0.21	-0.18
Δ_LC_01	0.18	**0.68**	0.28	-0.15
Δ_LC_02	0.14	**0.71**	0.31	-0.29
Δ_LC_03	0.13	**0.61**	0.26	-0.19
Δ_LC_04	0.04	**0.81**	0.38	-0.25
Δ_PA_01	0.20	0.05	**0.42**	0.04
Δ_PA_02	0.17	0.44	**0.82**	-0.22
Δ_PA_03	0.09	0.31	**0.69**	-0.22
Δ_PA_04	0.08	0.12	**0.42**	-0.08
Δ_PA_05	0.14	0.26	**0.67**	-0.09
Δ_NA_01	-0.19	-0.29	-0.22	**0.77**
Δ_NA_02	-0.10	-0.16	-0.15	**0.65**
Δ_NA_03	-0.15	-0.31	-0.23	**0.83**
Δ_NA_04	-0.10	-0.14	-0.01	**0.68**
Δ_NA_05	0.04	-0.11	-0.03	**0.55**
AVE	**1.00**	**0.50**	**0.39**	**0.50**
–	**1.00**	–	–	–
Δ_LC	0.17	**0.71**	–	–
Δ_PA	0.21	0.44	**0.63**	–
Δ_NA	-0.18	-0.32	-0.23	**0.71**

Table 4.10: Measurement Model Assessment for Model of Counterfactual Direction - CF_Dir = counterfactual direction, which is equivalent for the lucky and positive groups (downward), and for the unlucky and negative groups (upward); Δ_LC = change in lucky composite; Δ_PA = change in positive affect; Δ_NA = change in negative affect. See Table 4.2 for content corresponding to item labels used here.

Provided at top are Composite Reliabilities (Dillon-Goldstein's rho; ρ_c). In the middle section are item loadings (in bold) and cross-loadings, for each item in the model (item labels are to the left). In the lower section is the Fornell-Larcker table with AVE's (horizontally in bold), the square root of the AVE (diagonally in bold) and latent variable to latent variable correlations.

4.6.1.2 Structural Model Assessment

The structural model with β values for each path and R^2 values for each exogenous latent variable is presented in Figure 4.6. Model results are in agreement with regression results presented in Table 4.9. The β values in the model are of a moderate magnitude, ranging from 0.207 to 0.389 in the positive direction, and from -0.178 to -0.233 in the negative direction. For the paths to and from Δ_NA (change in negative affect) the β values are negative as would be expected (and consistent with the regression results previously).

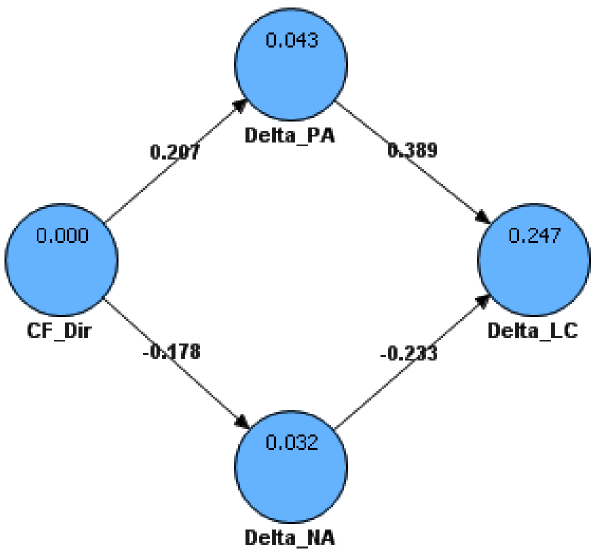

Figure 4.6: PLS Structural Model of Counterfactual Direction, PA, NA, and LC - Parameter estimates (path βs on the lines; R^2 values inside each construct) for a proposed PLS model of Counterfactual Direction (CF_Dir), change in positive affect (Delta_PA), change in negative affect (Delta_NA), and change in lucky feelings (Delta_LC).

As indicated by the non-significant (and therefore omitted) path from CF_Dir (counterfactual direction) to Δ_LC (change in lucky composite), counterfactual direction has no direct effect on change in lucky feelings when positive and negative affect are included in the model. When positive and negative affect are removed from the model, and the path from CF_Dir (counterfactual direction) to Δ_LC (change in lucky composite) is tested, the result is statistically significant ($p < .001$) with a β of 0.207 and R^2 of 0.043. This is an indication of mediation.

The R^2 values in Δ_PA (change in positive affect) and Δ_NA (change in negative affect) are quite weak, but the R^2 value for Δ_LC (change in lucky composite) is quite high. Approximately 25% of variance in the change in lucky feelings is accounted for by changes in positive and negative affect. The contribution of Δ_PA (change in positive affect) to that variance is somewhat greater than that of Δ_NA (change in negative affect), as indicated by the $Cohen's f^2$ values of 0.07 when Δ_NA (change in negative affect) is removed and 0.18 when Δ_PA (change in positive affect) is removed[1]

The model begs the question of mediation, and examining the total effects from CF_Dir (counterfactual direction) to Δ_LC (change in lucky composite) using 1) Δ_PA (change in positive affect) alone; 2) Δ_NA (change in negative affect) alone; and 3) Δ_PA and Δ_NA simultaneously revealed, respectively 0.09, 0.06, 0.12. The t-value for total effect through Δ_NA alone was marginal with only some runs (500 resamples) exceeding the 1.96 level. Given the non-significant direct path from CF_Dir (counterfactual direction) to Δ_LC (change in lucky composite), I expect that mediation is strong.

A combined VAF (variance accounted for) technique[2] confirmed that the majority of influence of CF_Dir (counterfactual direction) flowed through the two affect constructs, with 71% mediation through Δ_PA (change in positive affect) and Δ_NA (change in negative affect) simultaneously, when the direct path is included.

To recount briefly, the main findings from the analyses in this section are:

- A small amount of change in lucky feelings, as measured by change in the items making up the lucky composite, can be explained by counterfactual direction;
- Counterfactual potency does not explain any change in lucky feelings above and beyond counterfactual direction;
- Positive affect predicts change in lucky feelings;

[1]Cohen's f^2 (Cohen, 1988) is calculated as the ratio of the difference between the model with a focal predictor and another predictor(s) and the model without the focal predictor to the unexplained variance in the full model: $Cohen's f^2 = \frac{R^2_{fullmodel} - R^2_{partialmodel}}{1 - R^2_{fullmodel}}$. A lower value for f^2 indicates that the removed variable has a smaller contribution to the overall R^2. Cohen's f^2 values can be categorised as small (.10), medium (.25), and large (.40).

[2]$VAF_{Combined} = \frac{(a_{\Delta\_PA} * b_{\Delta\_PA}) + (a_{\Delta\_NA} * b_{\Delta\_NA})}{(a_{\Delta\_PA} * b_{\Delta\_PA}) + (a_{\Delta\_NA} * a_{\Delta\_NA}) + c'}$, where $a_{\Delta\_PA} = 0.207$; $b_{\Delta\_PA} = 0.389$; $a_{\Delta\_NA} = -0.178$; $b_{\Delta\_NA} = -0.233$; and $c' = 0.050$

- Negative affect also predicts change in lucky feelings, but relatively less well than positive affect;
- Positive and negative affect both mediate a relationship between counterfactual direction and change in lucky feelings;
- Counterfactual direction predicts change in positive and negative affect, though not very well;

I conclude that positive and negative affect are implicated in the change in lucky feelings arising from counterfactual direction. It appears however that positive and negative affect have other probable influences much stronger than counterfactual direction.

4.7 The Influence of Lucky Feelings and Affect on Overconfidence

To what extent do lucky feelings influence overconfidence? Are there differing effects for the different types of overconfidence? What role do positive and negative affect play?

In this section, I test both lucky feelings and affect as predictors of two different types of overconfidence. I also test the combination of belief in luck and lucky feelings as a predictor of overconfidence. I propose the final model for this chapter, which offers a foundation to understand the complex nomological net that includes belief in personal good luck, momentary lucky feelings, positive affect, negative affect, and two types of overconfidence.

I begin with a focused test of the direct relationships between the latent variables used in this section, in the form of a correlation matrix. Table 4.11 provides the correlations between variables used in this study. Correlations not significant at $p < .05$ have been omitted from the table and replaced with a '–'. When there is more than a single item, I have used the mean of the block of items for a given construct. For example, T2_LC (Post-trivia lucky composite) is the mean of the four items that make up the construct (i.e., T2_LC_01, T2_LC_02, T2_LC_03, and T2_LC_04).

The first result I call attention to is the lack of significant correlation between the valenced counterfactual potency (Val_CP) and any other item or measure in the matrix

	T2_LC	T2_PA	T2_NA	GBL	PGL	T1_OE	T1_OP	T2_OE	T2_OP
Val_CP	–	–	–	–	–	–	–	–	–
T2_LC	–	0.46	–	0.17	0.33	0.17	–	0.25	–
T2_PA	0.46	–	–	–	–	–	–	–	–
T2_NA	–	–	–	–	–	–	–	–	–
GBL	0.17	–	–	–	0.44	–	–	–	–
PGL	0.33	–	–	0.44	–	0.18	–	–	–
T1_OE	0.17	–	–	–	0.18	–	0.55	0.40	–
T1_OP	–	–	–	–	–	0.55	–	0.36	0.19
T2_OE	0.25	–	–	–	–	0.40	0.36	–	0.30
T2_OP	–	–	–	–	–	–	0.19	0.30	–

Table 4.11: Correlations: Overconfidence, Lucky Feelings, Affect and Belief in Luck - Presented are the correlations between overestimation and overplacement (adjusted) measure prior to and after the trivia task, measures for post-manipulation lucky composite, positive affect, and negative affect, a measure of the valenced counterfactual potency (mean). Correlations not significant at $p < .05$ have been omitted from the table and replaced with a '–'.

(see the first row of the table). In particular, it appears that Val_CP has no relationship with any of the overconfidence measures. A test of counterfactual direction alone also yielded no relationship to overconfidence measures. Taken with findings in the previous section, this is evidence that counterfactual direction and counterfactual potency play a much more limited role in luck phenomena than once thought. This claim is tempered by the results originating from only a single study (so far) and by counterfactual potency having been measured in only one way.

The post-manipulation lucky composite (T2_LC) correlates with three other measures in the matrix. As we saw in the previous model, there is a correlation with positive affect (T2_PA) of 0.46. The post-manipulation lucky composite (T2_LC) also correlates with general belief in luck (GBL) and personal belief in luck (PGL), which would be expected. This differential correlation of overestimation and overplacement with T2_LC lends a degree of validity to all three measures.

Looking for predictors of overconfidence measures, the post-manipulation lucky composite (T2_LC) is unique among those presented in the table with (moderate) correlations of 0.17 and 0.25 with Pre-trivia Overestimation (T1_OE) and post-trivia overestimation (T2_OE). Unsurprisingly, measures of overconfidence inter-correlate with one another in the moderate to strong range, from 0.19 (pre- and post-overplacement; T1_OP_adj and T2_OP_adj respectively) to 0.55 (pre-task overplacement and pre-task overestimation; T1_OP_adj and T1_OE respectively). Apart from other measures of overconfidence though, overplacement has no apparent predictors. Post-manipulation negative affect (T2_NA) also did not correlate with any other measure[1].

I now turn to a structural model to more clearly and thoroughly examine these relationships. Below I specify a model that demonstrates an interesting set of relationships between affect, lucky feelings, overestimation and overplacement. Rounding the model out is a belief in luck acting as a moderator for predictors of both types of overconfidence.

4.7.1 PLS Model of Affect, Lucky Composite and Overconfidence

I now use a PLS analysis to further address the aims of this section. Figure 4.7 presents the second and final model for this chapter. The model specifies belief in personal good luck (PGL), positive affect (PA) and negative affect (NA) as exogenous constructs that predict lucky feelings (LC). Each of these in turn predict both overplacement and overestimation. Recall that there were two measures of each overconfidence type: one prior to the trivia task and one after the trivia task. I will use separate constructs for each, for a total of four overconfidence constructs. An interaction of PGL and the Luck Composite is also included in the model as a predictor of the overconfidence constructs.

Because the data for Chapter 4 were collected prior to the publication of the additional 10 items in the BIGL22[2], there are only two constructs of luck belief that were collected from the experiment PGL and GBL. Recall that in Chapter 3, I concluded that items in GBL and PGL had questionable discriminant validity, so including GBL in the model presented later is counter to the recommendations of my earlier findings.

[1]Overplacement and post-manipulation negative affect emerge in the PLS model that follows as statistically significant. Because PLS does not force the simple mean of a scale for use as a variable [i.e., T2_LC = mean(T2_LC_01, T2_LC_02, T2_LC_03, and T2_LC_04)], the method is somewhat more sensitive to relationships in the data. Recall that Chin (1996) discusses the comparison of Type II errors across ANOVA, regression, and PLS, asserting that PLS has relatively greater power of detection.

[2]The BIGL22 added 10 items to the BIGL12. Five of those additional items are used to form the PBL construct. Thus, although the BIGL16 contains items for PGL, PBL, GBL and LIR, only PGL and GBL could be potentially used in the model in this chapter because only items from PGL and GBL were collected for the present study.

Regardless, PGL is the most appropriate construct to include here because it captures a belief regarding self-relevant luck outcomes.

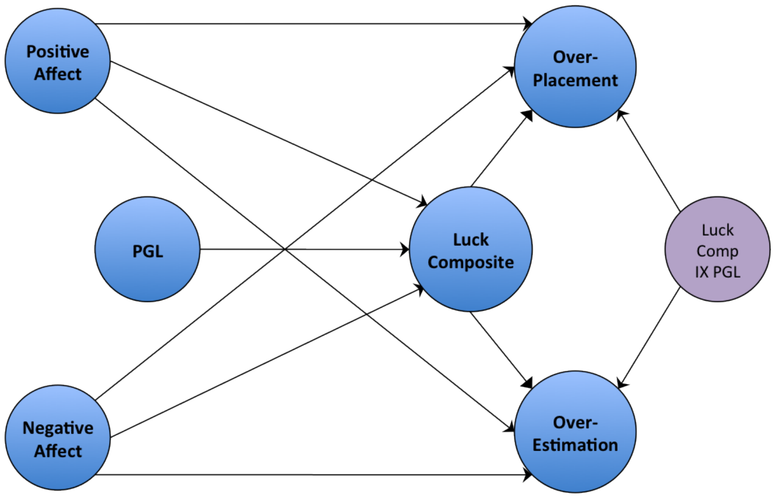

Figure 4.7: PLS Proposed Model of Affect, Lucky Feelings and Overconfidence - A proposed PLS model of belief in personal good luck (PGL), positive affect (PA), negative affect (NA), lucky feelings (LC), and two overconfidence constructs: overestimation and overplacement. Though overestimation is represented here as a single construct, two separate constructs will be created for both pre-trivia and post-trivia overestimation measures. This is also the case for overplacement. An interaction of PGL and the Luck Composite (Luck Comp IX PGL) is also included as a predictor of the overconfidence constructs. Note that the indicators for positive affect, negative affect, and lucky composite (respectively, T2_PA, T2_NA, and T2_LC) are those collected after the counterfactual priming manipulation.

Ideally, I would merge the model in Figure 4.5 with that presented here. However, because the previous model used change in lucky feelings and affect and the model below uses post-manipulation affect and lucky feelings, it is not possible to combine the two. The previous model sought to examine the impact of counterfactual thinking on positive affect, negative affect and lucky feelings. Controlling for individual differences in baseline using a change-score provides a more accurate assessment of the effect of counterfactual direction. The present model seeks to represent the impact of affect and lucky feelings on overconfidence. Using a change score in this model would test the relationship between overconfidence and the responsiveness of affect and lucky feelings to a manipulation.

Generally speaking the model proposes that positive affect, negative affect and the luck composite will predict two types of overconfidence. (I did not have specific hypotheses regarding the relationship of one type of confidence being better predicted by affect or luck.) In specific terms, I thought that positive affect and the luck composite should be positively associated with overconfidence, and that negative affect could be negatively associated with overconfidence. Given the results of the previous PLS analysis, I modelled both affect constructs as predictive of the luck composite. The interaction of the luck composite and PGL was formulated with the thought that a personal belief in luck was important in the transfer of a lucky feeling into an assessment of future or past performance of the task. Thus, higher PGL and higher LC should be associated with greater overconfidence.

4.7.1.1 Measurement Model Assessment

A single factor was extracted for each of the blocks of items comprising PGL, lucky composite, positive affect and negative affect. Figure 4.8 presents the measurement model with bootstrap t-values (500 resamples) for indicator loadings and paths. (Note that the arrangement of the constructs differs somewhat to the proposed model in the previous figure.) All indicator loadings were statistically significant at $p < .01$ except for T2_NA_02 (Hostile). I will leave this item in the model as it is part of a well-validated scale (Vinzi et al., 2010, p. 685; 695).

Internal reliabilities were acceptable for PGL, lucky composite (LC), and positive affect (PA) with composite reliabilities of 0.89, 0.87 and 0.86 respectively. NA was a little low at 0.64, probably because of T2_NA_02. Loadings were quite good, again with the exception of negative affect items, in particular T2_NA_02. Cross-loadings were within an acceptable range for most items. Some cross-loading occurred between positive affect and lucky composite, in particular T2_LC_04 had a 0.60 loading on positive affect (PA) and T2_PA_02 had a 0.57 loading on lucky composite (LC). The AVE's were acceptable for PGL, lucky composite (LC) and positive affect (PA). The AVE for negative affect (NA) was very low. All items passed the Fornell-Larcker criterion of AVE. In all cases the square root of AVE exceeds the latent variable correlations.

Both of the affect constructs had statistically significant paths predicting the luck composite construct, a finding consistent with the previous model that focused on the effect of counterfactual direction on change in positive affect, change in negative affect and change in the luck composite. The affect constructs did not have statistically significant paths to any of the overconfidence constructs (i.e., eight total paths). The luck

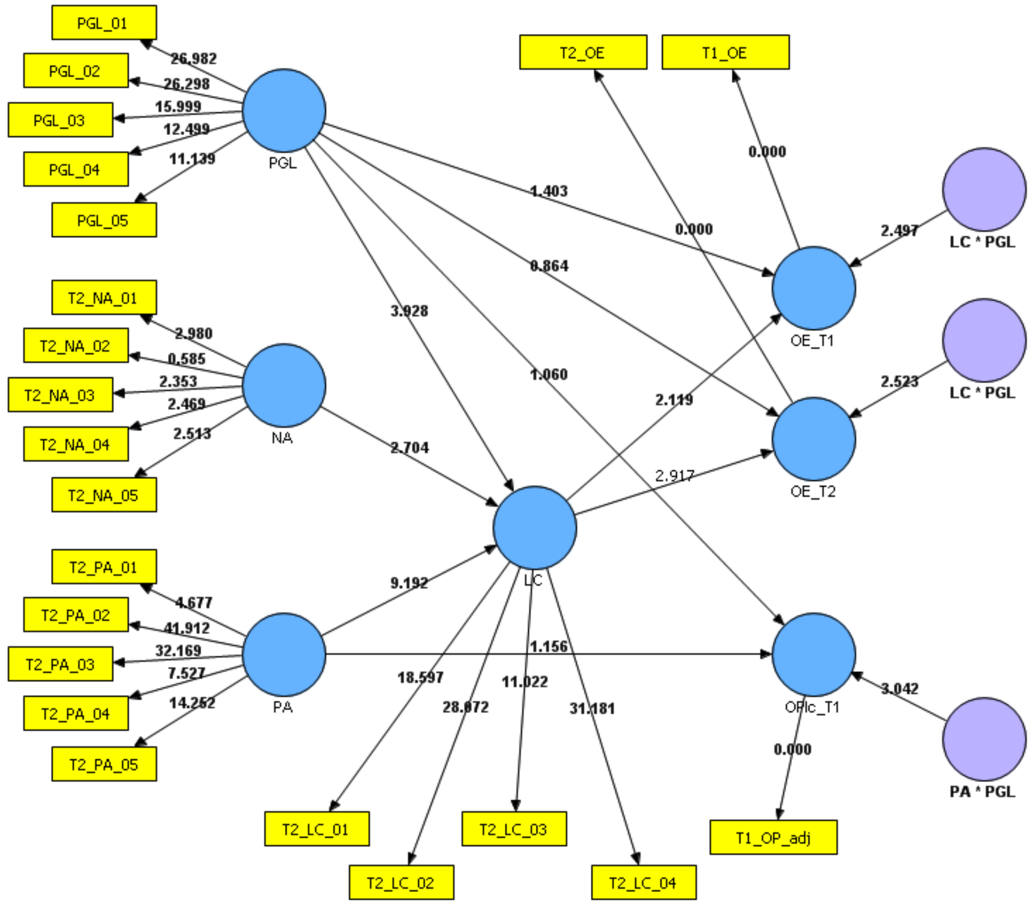

Figure 4.8: PLS Measurement Model of Affect, Lucky Feelings and Overconfidence - Bootstrap t-values (500 resamples) for the proposed PLS model in Figure 4.7. Only statistically significant paths are retained in this model, and any paths required to form an interaction term. The measurement model includes a subset of those indicated in the proposed model: Belief in personal good luck (PGL); positive affect (PA); negative affect (NA); luck composite (LC); overestimation before the trivia task (OE_T1) and after the trivia task (OE_T2); and overplacement at before the trivia task (OPlc_T1). Note that the indicators for positive affect, negative affect, and lucky composite (respectively, T2_PA, T2_NA, and T2_LC) are those collected after the counterfactual priming manipulation.

	PGL	LC	PA	NA	OE_T1	OE_T2	OPlc_T1
Composite Reliability	0.89	0.87	0.86	0.64	1.00	1.00	1.00
PGL_01	**0.86**	0.25	0.08	-0.08	0.16	0.07	0.04
PGL_02	**0.85**	0.26	0.01	-0.04	0.17	0.09	0.11
PGL_03	**0.78**	0.33	0.15	-0.11	0.19	0.10	0.07
PGL_04	**0.73**	0.22	0.00	0.01	0.13	0.14	0.10
PGL_05	**0.74**	0.25	-0.10	-0.07	0.08	0.09	-0.03
T2_LC_01	0.39	**0.79**	0.31	-0.19	0.11	0.25	0.03
T2_LC_02	0.32	**0.86**	0.35	-0.23	0.11	0.25	0.01
T2_LC_03	0.13	**0.68**	0.39	-0.08	0.11	0.11	0.02
T2_LC_04	0.22	**0.83**	0.60	-0.31	0.21	0.18	0.05
T2_PA_01	0.05	0.17	**0.50**	-0.12	-0.01	-0.11	-0.14
T2_PA_02	0.04	0.57	**0.88**	-0.20	0.16	0.12	0.10
T2_PA_03	0.00	0.47	**0.86**	-0.18	0.16	0.08	0.17
T2_PA_04	-0.01	0.18	**0.64**	-0.12	0.10	0.01	0.04
T2_PA_05	0.09	0.36	**0.77**	-0.22	0.12	0.12	0.03
T2_NA_01	-0.07	-0.20	-0.16	**0.83**	-0.10	-0.11	0.02
T2_NA_02	0.04	0.16	0.19	**-0.17**	0.06	0.09	0.09
T2_NA_03	0.05	-0.08	-0.01	**0.53**	0.02	-0.03	0.08
T2_NA_04	-0.09	-0.02	0.06	**0.62**	-0.03	-0.08	0.12
T2_NA_05	-0.11	-0.03	-0.02	**0.61**	-0.10	-0.11	0.12
T1_OE	0.19	0.18	0.17	-0.12	**1.00**	0.40	0.55
T2_OE	0.12	0.25	0.10	-0.16	0.40	**1.00**	0.36
T1_OP_adj	0.08	0.04	0.10	0.00	0.55	0.36	**1.00**
AVE	**0.63**	**0.62**	**0.56**	**0.35**	**1.00**	**1.00**	**1.00**
–	**0.79**	–	–	–	–	–	–
LC	0.34	**0.79**	–	–	–	–	–
PA	0.05	0.54	**0.75**	–	–	–	–
NA	-0.08	-0.28	-0.23	**0.59**	–	–	–
OE_T1	0.19	0.18	0.17	-0.12	**1.00**	–	–
OE_T2	0.12	0.25	0.10	-0.16	0.40	**1.00**	–
OPlc_T1	0.08	0.04	0.10	0.00	0.55	0.36	**1.00**

Table 4.12: Measurement Model Assessment for Overconfidence Model - PGL = belief in personal good luck; LC = post-manipulation lucky composite; PA = post-manipulation positive affect; NA = post-manipulation negative affect; OE_T1 and OE_T2 = respectively, pre- and post-trivia overestimation; OPlc_T1 = pre-trivia overplacement. See Table 4.2 for content corresponding to item labels used here.

Provided at top are Composite Reliabilities (Dillon-Goldstein's rho; ρ_c). In the middle section are item loadings (in bold) and cross-loadings, for each item in the model (item labels are to the left). In the lower section is the Fornell-Larcker table with AVE's (horizontally in bold), the square root of the AVE (diagonally in bold) and latent variable to latent variable correlations.

composite had a statistically significant path to both pre-trivia overestimation (OE_T1) and post-trivia overestimation (OE_T2), but not to either of the overplacement constructs. The interactions of the luck composite and PGL (LC*PGL) also had statistically significant paths to pre-trivia Overestimation (OE_T1) and post-trivia Overestimation (OE_T2). The PGL construct had a statistically significant path to the luck composite (LC), but not to any overconfidence construct. This is not surprising—the paths from PGL to the overconfidence constructs in Figure 4.8 were only included in order to create the interaction terms[1]. After running the proposed model, I attempted an interaction of PGL and positive affect on each of the overconfidence constructs (i.e., four total paths). The interaction was only significant for the pre-trivia overplacement construct. This is a post-hoc finding that was not anticipated, so this path is questionable, but I will investigate the pattern nonetheless to determine if it is similar to what I proposed for the luck composite*PGL interaction. With the exception of non-LC paths to the overconfidence constructs (i.e., PGL and PA), paths in the model are significant at $p < .01$.

I take the measurement model as adequate, with caution regarding the negative affect (NA) construct. This item is only used to predict lucky composite (LC) however, so any impact to the rest of the model is reduced. The measurement model is sufficient to confidently test the most interesting components—that overestimation in predicted by lucky feelings and an interaction with belief in luck, while overplacement may be predicted by the interaction of positive affect and belief in luck.

4.7.1.2 Structural Model Assessment

The structural model with β values for each path and R^2 values for each endogenous latent variable is presented in Figure 4.9. All path coefficients are in the expected direction. The β values for LC to the two overestimation measures are 0.154 and 0.248 for pre- and post-trivia overestimation respectively. There is no statistically significant path from PA (positive affect) to OPlc_T1 (pre-trivia Overplacement), reflected by the weak β. There was a moderately strong β value for the path from PGL to LC (lucky composite).

[1]Recall that constructs used to make interaction terms require a path from the direct effects constructs to the dependent variable paths, regardless of whether the direct effects are statistically significant. Thus path coefficients that are not statistically significant must be retained in the model. In the present model, there are four such paths: from PGL to the three overconfidence constructs; and from PA to the overplace-

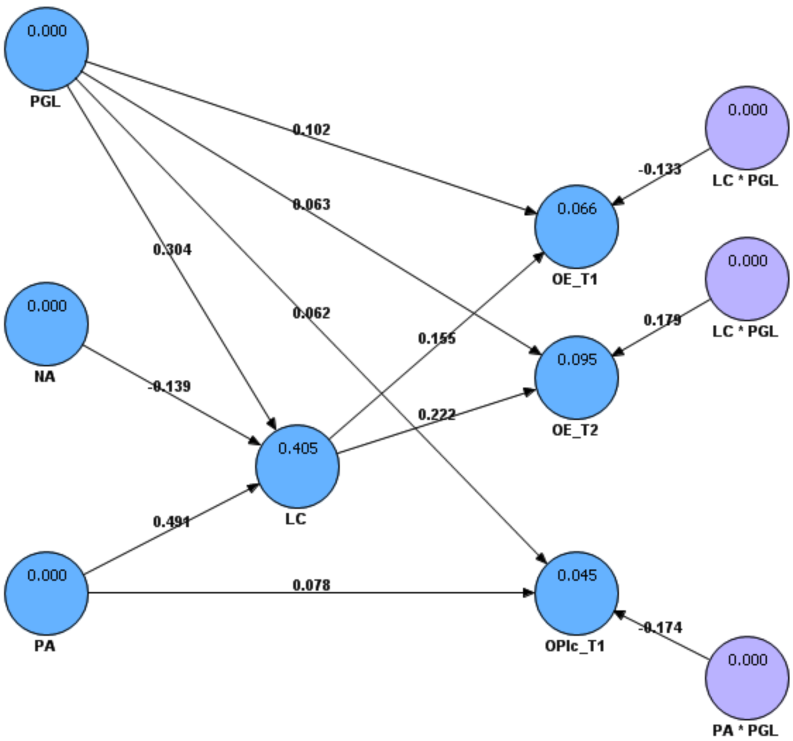

Figure 4.9: PLS Structural Model of Affect, Lucky Feelings and Overconfidence - Parameter estimates (path βs on the lines; R^2 values inside each construct) for a proposed PLS model of belief in personal good luck (PGL), positive affect (PA), negative affect (NA), lucky feelings (LC), overestimation prior to the trivia task (OE_T1), overestimation after the trivia task (OE_T2), and overplacement prior to the trivia task (OPlc_T1). Note that the indicators for PA, NA, and LC are those collected after the counterfactual priming manipulation.

Path coefficients for the three interaction terms will be discussed momentarily. A separate analysis is helpful to interpret the magnitude and direction of the β values, but more importantly the pattern of the interaction results. There are four endogenous constructs in the model, for which an R^2 is calculated. The R^2 value for LC (lucky composite) is high, while those for the three overconfidence measures are in a low range, but not practically insignificant.

4.7.1.3 Structural Model Discussion

I begin by calling attention to the moderately strong β value for the path from PGL to LC (lucky composite), 0.304. That PGL and LC are significantly related is in line with expectations. A belief in personal good luck should predict lucky feelings. Demonstrating that lucky feelings and affect are not the same, the other two paths from PGL – to positive and negative affect – did not reach statistical significance. Put simply, a belief in personal good luck predicts lucky feelings, but not affect. As mentioned previously, paths from the two affect constructs to the two overestimation constructs were not statistically significant and not retained in the final model. Neither was the path from lucky feelings to OPlc_T1 (pre-trivia Overplacement). This result argues again for the distinction between affect and lucky feelings.

Though the R^2 values are low for the three overconfidence measures, the result is useful in highlighting the distinction between affect and lucky feelings. The manner in which responses were collected cannot be credited with these differential effects: Recall that the four items comprising the lucky composite variable were appended to the PANAS items, and delivered in the exact same format. They were not set apart in the materials as being a separate section. Subjects would have had no idea there was a distinction between the lucky composite items, the positive affect items, and the negative affect items. Also, the evidence for a distinction between affect and lucky feelings is bolstered by the correlation between positive affect and lucky feelings, 0.491. That they are related to one another, but distinct in their relationship to other variables is important to note. I assert that lucky feelings are not just a proxy for positive affect.

Another analysis—not presented here—tested the model with one additional indicator for each of the three overconfidence measures. Recall that I elicited esti-

ment construct.

mates of the lower bound for 90% confidence range for self and other performance (See Table 4.1). Thus, I was able to include as an additional measure for OPlc_T1 (pre-trivia Overplacement), a 'low' indicator. Likewise, for OE_T1 (pre-trivia Overestimation) and OE_T2 (post-trivia Overestimation) I could include 'low' indicators, namely T1_OE_low and T2_OE_low. Including these three 'low' indicators resulted in two changes to the model results that are noteworthy. The first is that the R^2 values for the three overconfidence measures increased slightly to 0.079, 0.103, and 0.065 for OE_T1 (pre-trivia Overestimation), OE_T2 (post-trivia Overestimation), and OPl_T1 (pre-trivia Overplacement) respectively. The second noteworthy change is that the t-value for the path from PA (positive affect) to OPlc_T1 (pre-trivia Overplacement) nears marginal significance. Depending on the bootstrap run, the path coefficient is sometimes significant at the $p < .05$ level, and sometimes was not. This is an unstable result, but is supportive of a possible relationship between positive affect and overplacement. Attendant with this near-effect would be a double dissociation for affect and lucky feelings on overestimation and overplacement.

To examine more closely the role of PGL in the model, I ran another analysis of the model using two indicators for each of the overconfidence constructs, and replaced general belief in luck items for belief in personal good luck items. The three interaction terms, now for GBL-PA and GBL-LC, were rendered statistically non-significant at traditional thresholds[1]. These results suggest that it is the belief in personal good luck, and not the general belief in luck that activates positive affect and lucky feelings with respect to overconfidence.

Turning our attention to total effects[2] in the model, only four are relevant for the discussion. They are the two affect constructs' relationship to the two overestimation constructs via LC (lucky composite). The path from NA (negative affect) through LC (lucky composite) to both OE_T1 (pre-trivia Overestimation), and OE_T2 (post-trivia Overestimation) were not statistically significant. However, the path from PA (positive affect) through LC (lucky composite) to OE_T2 (post-trivia Overestimation) was statistically significant at 0.109 with a t-value of 2.92. The path from PA (positive affect)

[1]The t-values were within the range of 1.6 to 1.7, hovering around the $p < .05$ threshold for a one-tailed test (1.64).

[2]Recall that total effects are the multiple-path coefficient values, and those values, along with bootstrap t-values are reported in PLS output.

through LC (lucky composite) to OE_T1 (pre-trivia Overestimation) was marginally significant at 0.076 with a t-value of 1.94.

A test for mediation would answer the question of whether lucky feelings is a *mechanism* for positive affect, either in part or in whole. Note that the (non-parametric) total effect t-value accomplishes a similar effect as a traditional (parametric) Sobel test which is to calculate a significance statistic for the combined paths, usually denoted 'a' and 'b'. Calculation of the z-statistics using Sobel's equation demonstrates a divergence from these bootstrap results just above: the z-statistics for pre- and post-trivia overestimation are 2.03 and 2.02 respectively. Although the results are similar, for pre-trivia overestimation, the two statistics are separated by the traditional threshold of $p < .05$, with the non-parametric result being more conservative. Relying solely on the non-parametric approach, only the total effect from PA (positive affect) to OE_T2 (post-trivia Overestimation) via LC (lucky composite) is significant, so there are mixed results as to whether lucky feelings act as a mechanism for positive affect.

Turning to the interaction terms in the model, the interaction effects represented a considerable amount of the variance explained in each of the three overconfidence measures. When the interaction terms are removed the R^2 values drop to 0.050, 0.064, and 0.015 for OE_T1 (pre-trivia Overestimation), OE_T2 (post-trivia Overestimation), and OPlc_T1 (pre-trivia Overplacement) respectively. The path coefficients are similar in magnitude, though they differ in sign. These β values are not easily interpretable, so I provide graphs to clarify the effects. To generate the data for the graphs, I first took the mean of each block of items for PGL, PA (positive affect) and LC (lucky composite) measured at post-manipulation. I then generated a median-split variable for PGL, PA (positive affect) and LC (lucky composite), denoting whether a given subject was above or below the mean for each.

In the case of OE_T1 (pre-trivia Overestimation), I computed the mean of OE_T1 for each of four groups represented in the two by two matrix of LC (high lucky composite and low lucky composite) and PGL (high and low). I then plotted these means to generate the graph in Figure 4.10. This same procedure was repeated for OE_T2 (post-trivia Overestimation, and a graph of the means in presented in Figure 4.11[1]. In each

[1]Throughout this thesis, graphs of median splits are presented for illustrative purposes. In all instances where median-splits are presented, the PLS bootstrap has previously confirmed the statistical significance of the interaction term.

of the two graphs, the high PGL-high LC (lucky composite) group is the bar to the rightmost of the figure.

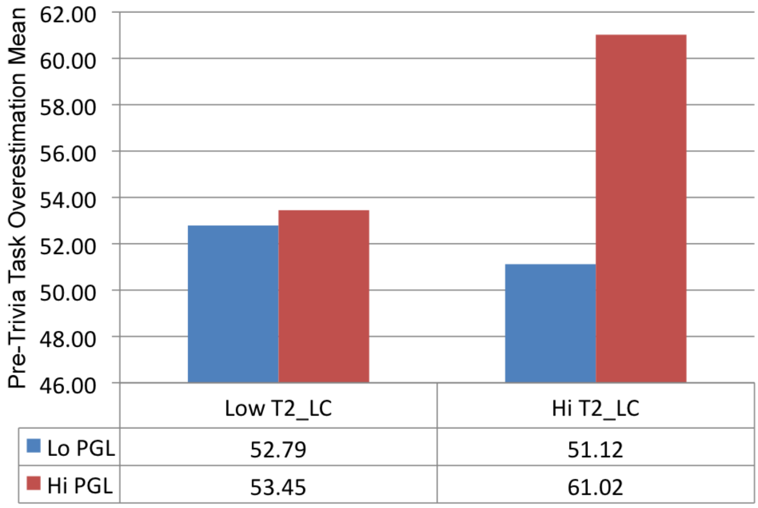

Figure 4.10: Pre-Trivia Overestimation Means, by median-split PGL and LC Groups - A bar graph demonstrating the significant interaction effect seen in Figure 4.8. The dependent variable is pre-trivia overestimation (T1_OE). On average, High PGL, High LC (lucky composite) individuals scored much higher on T1_OE (pre-trivia overestimation) than did others, indicating the it is a combination of both belief in luck and lucky feelings that influences overestimation.

For pre-trivia Overplacement (OPlc_T1), I computed the mean of OPlc_T2 for each of four groups represented in the two by two matrix of PA (high and low) and PGL (high and low), where high and low groups were defined by a median-split. I then plotted these means to generate the graph in Figure 4.12. In this graph, the high-PGL-high PA (positive affect) group is the bar to the rightmost of the figure.

All three interactions show a similar pattern: a belief in personal good luck moderates the relationship of positive affect and overplacement, and moderates the relationship of lucky feelings and overestimation, such that the combination of high PGL and high PA or high LC predicts higher overplacement or higher overestimation respectively. Those who report a higher belief in luck are more likely to report overplacement if they are high in positive affect. Also, those who report a higher belief in luck are more likely to report higher overestimation if they are high in lucky feelings. Put another way, the feeling of the moment, in this case positive affect and lucky feelings, *activates* an existing belief in personal good luck in the context of overconfidence.

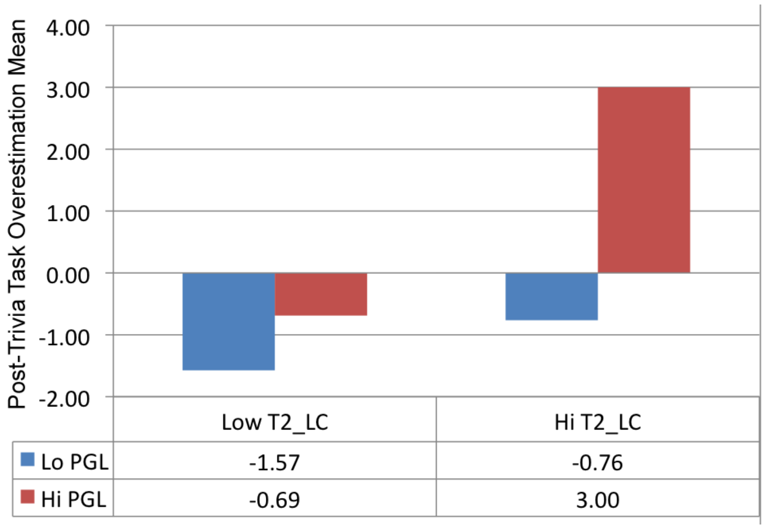

Figure 4.11: Post-Trivia Overestimation Means, by median-split PGL and LC Groups - The dependent variable is post-trivia overestimation (T2_OE). A plot of post-trivia overestimation for median-split PGL and LC (lucky composite) groups demonstrates the same pattern of effect as that seen in Figure 4.10, namely that High PGL, High LC (lucky composite) individuals scored higher on overestimation than did the others.

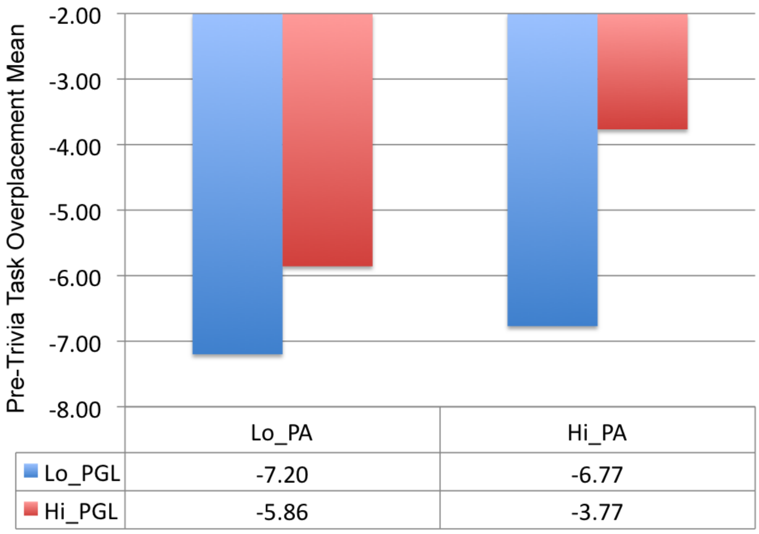

Figure 4.12: Pre-Trivia Overplacement Means, by median-split PGL and PA Groups - The dependent variable is Pre-Trivia Overplacement (T1_OPlc_adj). A plot of T1_OPlc_adj for median-split PGL and PA groups demonstrates the same pattern of effect as that seen in Figures 4.10 and 4.11. Note here however that all groups are reporting an underplacement, but that High PGL, High PA subjects, on average report less underplacement.

Recall that for difficult tasks, people generally overestimate and underplace their performance. How did the results accord with this general pattern? Only one single construct, overestimation after the trivia task (OE_T2) could be potentially informative because the others were either prior to the trivia task (before there was any feedback about task difficulty) or there were no significant predictors (as in the case of overplacement after the trivia task). It appears that lucky feelings as measured by the luck composite has a tendency to exacerbate the general pattern, and this is further compounded by belief in luck (PGL). This is a potentially useful finding for the area of overconfidence. For the study of luck, it indicates that lucky feelings have a buffering effect against feedback: an indication of task difficulty appears to be incorporated to a lesser extent when a person feels lucky, and even more so with that lucky-feeling person have a stronger belief in luck.

There is an interesting pattern that emerges when pre-trivia overestimation is compared to post-trivia overestimation. The effect of task experience on each of the four groups is demonstrated by comparing the individual bars in Figures 4.10 and 4.11. Note that the absolute level of overestimation falls dramatically for all groups. The scale to the left of the graphs for the first figure ranges from 46 to 62, whereas the scale for the second graph ranges from -2 to 4.

Note also that in the first figure, all groups overestimate their pending performance, OE_T1 (pre-trivia Overestimation). In the second figure however, only the high PGL-high LC (lucky composite) group persists in overestimation. The other three groups move into the range of underestimation. The graphs are only illustrative, so I caution against over-interpretation.

To recount briefly, the main findings from the analyses in this section are:

- Positive affect and lucky feelings do not predict the same types of overconfidence;
- Lucky feelings predicts overestimation;
- Positive affect *may* predict overplacement (Recall that when OPl_T1 consists of both a point estimate and the lower estimate of a 90% confidence range, the path from PA to OPl_T1 nears marginal significance.);
- A belief in personal good luck does not have a direct effect on either overestimation or overplacement;

- A belief in personal good luck *does* moderate the relationship of lucky feelings and overestimation;
- A belief in personal good luck *does* moderate the relationship of positive affect and overplacement, a finding unexplainable by any theory I'm aware of.

I conclude that it is important to take into account both affect and lucky feelings when exploring overconfidence. It is important to closely examine different types of dependent variables relative to both affect and lucky feelings. The moderating role of belief in luck is also important to take in account in the study of luck cognitions.

4.8 Chapter Discussion

The study reported in this chapter measured the effect of a retrospectively-oriented manipulation on lucky feelings and overconfidence. The counterfactual priming manipulation required participants to recall a past event that they personally experienced and then list ways in which the outcome could have been different. The measure used for lucky feelings was a four-item composite that drew on different dimensions of judgements of lucky feelings, as described in Wagenaar & Keren (1988). The lucky feelings composite contained two items (i.e., 'lucky' and 'fortunate') that could potentially differentiate between two different types of previously identified lucky feelings: luck-expectancy and luck-gratitude. However, several tests demonstrated these two items to be near substitutes for one another despite having a correlation that ranged from 0.32 to 0.61. As a final check for differences between these two items, I altered the lucky composite construct and conducted bootstrap tests of statistical significance for paths in each of the two PLS models above. In the first run, I removed only the item corresponding to 'lucky'. In the second run, I removed only the item corresponding to 'fortunate'. So, for each run, the lucky composite construct had three indicators. There were no changes to the levels of statistical significance for paths from constructs that contained the removed item. This highlights further that—at least in the context of personally recalled events and counterfactual events—lucky and fortunate may serve as substitutes for one another. Thus, this chapter provides no support for the distinction between the two types of lucky feelings.

I now revisit Figure 4.1 introduced on page 133, which contained the different possible types of relationships between lucky feelings, affect and a dependent variable. Sub-figure A is precluded by the findings above. Lucky feelings and affect are not unitary, as demonstrated by only moderate correlations between them. Sub-figure B is seen where PA predicts LC as well as Overplacement in the second model. However, the simple conclusion that affect and lucky feelings are merely two different words that describe the same phenomenon is untenable given the whole of the results. Clearly, because affect and lucky feelings are predicting different types of overconfidence, they cannot be judged as the same. The moderately strong correlation between affect and lucky feelings might indicate this. But as I've concluded above, the remainder of the evidence supports a view that lucky feelings are not merely a poor proxy for affect, nor vice versa. Evidence from other research also argues for this view: Using a wheel of fortune paradigm, Wohl & Enzle (2003) manipulated lucky feelings while affect remained unchanged.

Although I thought it would be one of the more likely results, there is only mixed evidence that sub-figure C emerged in the model. The total effect path from positive affect (PA) to post-trivia Overestimation (OE_T2) via lucky composite (LC) was statistically significant indicating mediation, while the path from positive affect (PA) to pre-trivia Overestimation (OE_T1) via lucky composite (LC) was not. Positive affect (PA) had a significant total effect to pre-trivia Overestimation (OE_T1) and not to post-trivia Overestimation (OE_T2), I would have more confidence in asserting that lucky feelings might be a mechanism for positive affect. However, given the interaction effect of PGL and LC (lucky composite), it seems that lucky feelings and affect share a similar quality: activation. I develop this thought further below. Sub-figure D did not emerge in the model. In no case does affect predict overconfidence simultaneously with lucky feelings.

There is marginal support that sub-figure E was found in the model. Recall that positive affect was near statistical significance in its prediction of OPlc_T1, and that when a second indicator was added to the overplacement construct, the path did reach significance. Important to note here though, are the non-significant paths from positive affect (PA) to overestimation and from lucky composite (LC) to overplacement. The differential prediction of the different types of overconfidence by interaction terms containing either PGL and positive affect (PA) or PGL and lucky composite (LC) may be interpreted as a weak form of double dissociation (sub-figure E). Though given the results, I can only suggest this is a possibility worthy of further investigation.

I close with a summary and some guiding commentary for future theoretical and empirical efforts in this area. In Figure 4.13 I have merged findings from the PLS two models and attempted to capture the basic essence of the findings reported in this chapter, as supported by the data from the counterfactual priming study. This summary model integrates counterfactual thinking, belief in lucky, affect, lucky feelings and overconfidence.

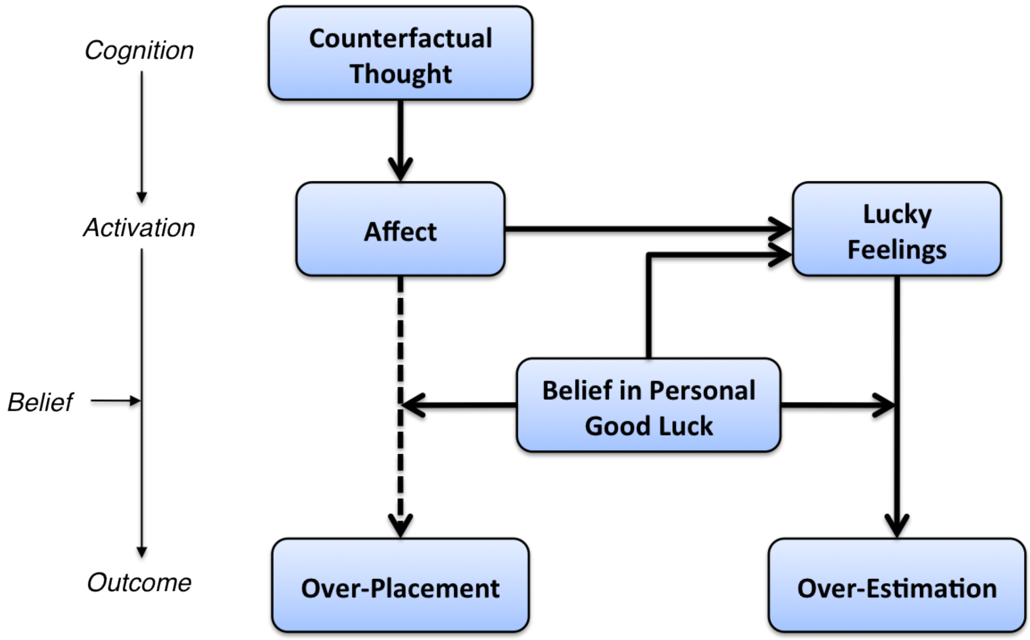

Figure 4.13: A Summary Model - A summary model for the results presented in this chapter. At a most basic level, the models specified herein take the form of the process to the left, where cognition results in an activation, which then interacts with a belief to yield an outcome. Note that positive and negative affect have been combined here, and that the path from affect to overplacement is dotted, indicating a tentative relationship.

To the left of the figure, I propose a generic description of the process that gives rise to an 'effect' of lucky feelings. To the right of that process is the corresponding nomological net that emerged from the two models in this chapter. Lucky feelings begin with a cognition, a thought. This cognitive event is comparative, counterfactual, in nature though may include other types of thought. Counterfactual potency doesn't seem to be linearly related to the next stage in the process, activation, though that assertion is based on only one measure of counterfactual potency. Activation takes two forms in this study presented in this chapter: affect and lucky feelings. Affect is clearly related to lucky feelings, though it may be the case that both are merely related along the activation dimension and predicated by some other second order or independent variable.

This is moderated by a belief, and depending on how one prefers to view it, either the belief *moderates* the activation, or the activation *moderates* the belief. Analogies of this abound: a belief in god may result in prayer in a dark hour; a belief in a particular diet may result in different eating habits in the face of a recent weight gain; a belief in a hypothesis may result in a study given a pilot result. These can all be seen as forms of a much broader system of expectancy motivation. Some outcome results from cognition, activation, and belief. In the case of this study, that outcome was overconfidence. It is interesting that lucky feelings primarily are associated with overconfidence that relates to absolute performance. Recall the findings of Merkle (2011) regarding overestimation: it was found to be related to a view that a portfolio was less risky than it appeared to be in terms of both portfolio volatility and returns. In light of those findings, it appears that lucky feelings impacts on the extent to which an individual accounts for a range of possibilities, a narrowing effect regarding negative outcome scenarios. Lucky feelings did not appear to be related to overplacement, what is sometimes called the 'better-than-average' effect. So feeling lucky perhaps doesn't influence a person to think he or she will win against someone else, but only that he or she will win against the odds. Other outcomes related to risky choice will be explored in the next chapter.

4.9 Limitations

A number of limitations to the study reported in this chapter are readily acknowledged. Firstly, the repeated measurement of affect and luck composite may have led to a demand response. The is especially the case with the rather transparent nature of the study, especially in the lucky and unlucky treatment conditions where the words 'lucky' and 'unlucky' were used repeatedly in the stimulus materials. Perhaps future research will address the inherent hypothesis guessing that results from open use of the terms lucky and unlucky, in the measurement of reactions to outcomes.

Secondly, there was a wide range of responses to the experimental manipulation. For some, recalled stories were much more rich and meaningful than others. Thus, the reaction that a participant may have had to his or her recalled story may have differed merely due to the story recalled. Presumably, random assignment to condition would have addressed this concern, but it is possible that a systematic bias by condition in the vividness or meaningful of recalled stories that was unrelated to the underlying nature of luck.

Thirdly, the primary dependent variables of overplacement and overestimation may have been subject to a confounding of skill. I note that a local culture of 'Trivia Night' held in various pubs near the university may have biased either the sample that signed-up, the measures themselves, or both. However, those who consider themselves skilled at trivia would presumably been less influenced by lucky feelings or affect–that is to say, this threat to validity could reasonably be expected to have an attenuating effect.

A final limitation concerns that lack of definitive separation of affect from luck feeling, as well as the absence of measures for unlucky feelings. Clearly, this is a limitation that constrains the conclusions that can be made. There was also little to differentiate effects in the positive condition from those in the lucky condition. Likewise, there was little to differentiate effects in the negative condition from those in the unlucky condition. Nevertheless, the summary model presented in Figure 4.13 is, I suggest, within the bounds of what can be reliably established from the results. As such, the model represents an advance in the understanding as outlined in the next section.

Generally speaking, this main weakness of this study is that it does not clearly distinguish between the two senses of luck, namely retrospective versus prospective. The manipulation was ostensibly of a retrospective nature, but the outcome variable relating to overconfidence were more in line with what would be expected of a prospective-type of luck feeling. The study in Chapter 5 attempts to remedy this shortcoming.

4.10 Chapter Conclusions

The first aim of this chapter was to examine counterfactual thinking as an origin of lucky feelings, including affect as an alternative explanation. The results of the study described in this chapter indicate that counterfactual direction, but not counterfactual potency has an impact on lucky feelings, but that effect is almost entirely mediated by affect. The first model presented clearly supports that view, as does a more traditional hierarchal regression approach.

The second aim of this chapter was to examine the influence of lucky feelings on overconfidence, again including affect as an alternative explanation. The second model presented in this chapter shows a complex set of inter-relationships. Overconfidence is not a unitary construct, and it is not unitarily predicted by either affect or by lucky feelings. It appears that lucky feelings generate overconfidence relative to objective standards (i.e., overestimation), while it is positive affect that may predict overconfidence relative to others (i.e., overplacement). A very important component of the model though is the moderating effect that a belief in personal good luck has on both overestimation and overplacement.

The use of PLS is a novel approach to the topic, allowing a broader view of the constructs in a nomological net. So PLS is both a methodological and interpretative improvement over existing approaches. Furthermore, a number of interim conclusions regarding the usefulness of the measures and protocols of the study refine the study of luck. I carry these forward into the study reported in the next chapter. I hasten to add that the results reported herein contain some low R^2 values, and the approach is an exploratory one. Attempts at replication and refinement of measures are recommended for future research in this area.

Chapter 5

Competition, Lucky Feelings, and Risky Choices

5.1 Chapter Aims and Overview

There are five primary aims of this chapter. The first is to shift focus to prospective-type lucky feelings and their influence on risky choice. The study reported in this chapter uses on a manipulation that was designed to primarily trigger prospective-type lucky feelings. Participants played a competitive game of chance in pairs, which resulted in one participant experiencing a win-outcome and another participant experiencing a loss-outcome. The consequences of the outcome are real and immediate, but not significant enough to invoke feelings of being fortunate or grateful. This is in contrast to the study in the previous chapter that used a manipulation of a retrospective nature, where participants recalled a significant life event and then generated counterfactuals. Differences in the patterns of findings across the two studies have the potential to inform the question of differentiating between the two previously identified types of lucky feelings: luck-expectancy and luck-gratitude.

The second aim is to continue an examination of the counterfactual closeness hypothesis. Counterfactual closeness remains an important issue in the present study, despite previous study results that indicate closeness has no greater explanatory power than does direction. It might be that counterfactual closeness impacts prospective-type lucky feelings differently than it does retrospective-type lucky feelings. The present study uses a different measure of counterfactual closeness, one that naturally varies for each participant dyad as a function of the mechanism used to generate the game outcomes (i.e., number of dice rolls). Thus, winning or losing represents the counterfactual direction, whereas how close the game outcome was (i.e., won by a single roll) represents counterfactual closeness. A subjective measure (participant rating of 'game closeness') and an objective measure of closeness (actual rolls) can be compared against each other in their relation to other study variables.

The third aim is to continue the inclusion of luck beliefs as moderators of prior outcomes and lucky feelings, or prior outcomes and risky choice. Belief in luck is expanded in this study to include the belief in personal bad luck (PBL), which mirrors belief in personal good luck (PGL). I use the five-item constructs for PGL and PBL that were validated in Chapter 3. I also include a measure of *un*lucky feelings in the present study, to mirror lucky feelings. The combination of the two personal luck beliefs and the two lucky feelings provides a symmetric expansion to luck beliefs and lucky feelings: PBL compliments PGL; and unlucky feeling compliments lucky feeling.

The fourth aim is to test the influence of lucky feelings on different types of risky choice. The previous chapter investigated the impact of lucky feelings on overconfidence, which could be one mechanism by which lucky feelings operates on risky choice. In this study, I take measures of confidence in a gamble, as well as the levels of investment in a gamble. In addition to gambles that resemble the domain in which a participant experienced the win or loss, I also include risky choice in a lottery context, a health context, and finally ambiguity tolerance in a gamble, as operationalised by preference for a gamble with known odds versus a gamble with unknown odds.

It is possible to combine and summarise these aims into a general model:

$$\textsc{Outcome} \times \textsc{Closeness} \times \textsc{Belief} \;\rightarrow\; \textsc{Feeling} \;\rightarrow\; \textsc{Choice}$$

The model is not without precedent. The counterfactual closeness hypothesis is essentially a statement that outcome (i.e., counterfactual direction) and closeness interact to generate an effect on lucky feelings (and more distally, risky choice). In analytical terms, outcome and closeness can be modelled as an interaction term, which is reflected by "Outcome $\times$ Closeness" in the general model above. Moreover, the empirical consideration of luck belief as a moderator is a decades-old practice (Darke, 1993). However, combining the three elements is theoretically compelling, yet analytically challenging. This is all the more challenging when luck belief and lucky feeling are expanded to include both good and bad luck beliefs and lucky and unlucky feelings—the symmetric expansion referred to above.

To clarify the analytic difficulty, a traditional regression approach is preferable to a univariate anova one given the continuous variables of belief and closeness. The interaction terms call for standardised product-interaction regression terms. But when the model is expanded to include good and bad luck beliefs and lucky and unlucky feelings, it contains *two* three-way interactions. The effect of those two three-way interaction terms on different types of risky choice would then be mediated by two different luck feeling types. So, the fifth aim of this chapter is to test the expanded model above in such a way that results can be communicated in an elegant and easily interpretable manner. At issue are conclusions regarding the influence of lucky feelings on risky choice, a comprehensive test of the counterfactual closeness hypothesis, an understanding of the relationship of lucky and unlucky feelings to each other and risky choice, and an integration of luck beliefs into the broader system of variables.

I begin the chapter by describing the experiment and method in detail in Section 5.2. At the end of that section I describe the features of the game, that is, those elements of the game that were included in order to examine the research questions. In Section 5.3 I describe each of the dependent variables, closing with a description of the features of those dependent variables. In Section 5.4, I present preliminary analyses. The first compares different closeness measures, testing for linearity in subjective perceptions of closeness versus two objective measures of rolls difference. The second preliminary analysis explores participant attributions of the game outcome to skill, luck, and chance. A final analysis in this section looks at the relationship of subjective closeness to luck beliefs. In Section 5.5 I use ANOVA and hierarchical regression to test for main effects of game outcome, closeness and luck beliefs on lucky feelings and risky choice. This is followed by a hierarchical regression model of the combined effect of game outcome and closeness on lucky feelings to test for incremental variance explained by closeness; a focused test of the counterfactual closeness hypothesis. Concluding this section is a test of the interactive effect of game outcome and different closeness measures on lucky feelings. In Section 5.6, I split the sample by game outcome, and model the whole system of variables using PLS for loss-outcome and win-outcome participants separately. I examine the mediating role of lucky feelings in the models, and finally conduct tests for differences between path coefficients in the models. A general discussion concludes the chapter in Section 5.9.

5.2 Method

The study was approved by the University of Sydney Human Research Ethics Committee (HREC Approval #11609 and modifications). The study consisted of approximately ten minutes of surveys, a game played in-person between two subjects to establish a win or lose outcome for each member of a participant dyad, and finally questions that probed the dependent variables of the game outcome. On average, the study lasted approximately 25 minutes.

5.2.1 Sample and Equipment

A total of 235 undergraduate psychology students at the University of Sydney participated in the study for extra credit. However, the final sample was reduced to 178 as a result of two criteria. Firstly, not all participants played another participant. Sometimes there were an odd number of participants in a session. When that occurred, one participant would play the experimenter. Secondly, I unfortunately lost a portion of the early data as a result of experimenter error in the procedure for saving. I lost only a single member for each dyad (always the winner), but for the losers, whose data I did have, I was unable to calculate a number of dyad-level variables. Thus, I made the decision to drop these as well, resulting in the 178 participants, who were paired together in 89 dyads. All materials were delivered on 19 inch LCD monitors via Windows Internet Explorer using javascript and html.

5.2.1.1 Purposive Recruitment via Pre-Screening

As in previous studies, participants were recruited from the University of Sydney psychology student subject pool, SONA. Students receive course credit—up to a maximum of four credits—for participating in studies offered via SONA. One credit is earned for each hour of participation. Participants for this study were purposively recruited with respect to belief in luck. The most advantageous aspect of purposive recruitment is that I would require a smaller number of subjects to detect a given effect, thereby limiting my use of university resources, namely participants in the subject pool, who are usually in quite high demand.

When students registered with SONA, they were provided with an opportunity to respond to pre-screening questions for later studies. Doing so provided participants with one-quarter of a credit. This pre-screening allowed researchers a means for targeting subjects for either inclusion or exclusion in a study based on some criterion response or responses. Researchers were not provided any information regarding an individual subject or their responses to the pre-screening. If a student qualified for a given study, that study simply appeared in the list of possible studies he or she could choose. Otherwise, the studies that a student did not qualify for were not present in the list.

For the present study, participants were pre-screened using their responses to the BIGL12. In accordance with Darke & Freedman (1997a), the appropriate items were reverse coded, and then the sum of the 12 items was calculated. I chose the BIGL12 because application for pre-screening preceded any conclusive results from work on the Belief in Good Luck Scale (BIGL16). The lead time for including a set of questions in pre-screening was quite long given that approval was required of not only the university ethics committee, but also the SONA administrator. (Recall that data from this present study were used in the validation effort reported in Chapter 3).

For any given pre-screening criterion, such as a particular cut-off score on a scale, it was possible for experimenters to view a count of qualifying participants. So I entered each possible score, from 12 (i.e., 1 x 12) to 60 (i.e., 5 x 12). I took the total and then divided the distribution into approximately thirds. I advertised a study for the low (i.e., bottom tertile) belief in luck participants, and a separate study for high (i.e., upper tertile) belief in luck participants. In this way I could exclude the middle tertile, and examine more efficiently the impact of luck beliefs on various dependent variables.

I wanted to prevent participants from knowing the study was about luck, and so provided a vague description. The study was advertised under the short title of "Conditions Affecting Decision Making". A short brief followed which said:

> This study is about influences on decision making. What makes us do what we do and think what we think? You'll do a brief survey to begin, then you'll play a game against another participant. After the game, there are a few more questions.

The only difference in the advertisements for the low and high BIGL12 groups was that for the low GIBL group I added a dash, "–", between 'Decision' and 'Making' in the title. This was so that I could tell the difference between lab sessions for low and high BIGL12 participants. I alternated between low and high BIGL12 sessions when scheduling. Participants would have had no awareness they were selectively recruited on the basis of the BIGL12.

Each session contained only low or high BIGL12 participants, mainly as a matter of convenience to me in scheduling. There would have been no foreseeable benefit to matching high and low BIGL12 participants in dyads. On the contrary, I thought it would be somewhat advantageous to have dyads that were paired by high-high or low-low BIGL12 so as to maintain an even allocation of independent variables of game outcome and belief in luck. By pairing high-low BIGL12, I would not have had a means of controlling the random game outcome, and could have ended up with a sample containing, for example, more high BIGL12 winners that low BIGL12 winners.

5.2.2 Pre-Manipulation Surveys

To begin the study, participants were welcomed into the lab, provided information regarding the study, and asked to complete consent forms. The number of participants (retained in the final dataset) during a session were two (44 participants), four (92 participants), and six (42 participants).

Participants were not allowed to start until everyone scheduled for a session had arrived, or until five minutes after the scheduled time, at which point any latecomers were not allowed to enter the lab. I did this because I wanted everyone to finish the pre-manipulation surveys at around the same time, so that the next portion of the study (the game) could be started simultaneously by everyone. The instructions for the Dice Game required a couple of minutes to explain, and I wanted to provide them only once without interrupting those who might not have otherwise completed the surveys.

The surveys consisted of some basic questions about demographics (gender, language spoken at home, and age) the BIGL22[1] and questions asking how lucky or unlucky they felt at that present moment. Although I had pre-screened participants based

[1]A regulatory focus scale and the PANAS were included after the BIGL22, but are not included in the analyses reported in this chapter. They were intended for validation efforts of the BIGL22 reported in Chapter 3.

on their BIGL12 responses, department policy did not allow for access to pre-screen responses by subject, so I could neither use their BIGL12 responses as an IV, or run test-retest comparisons on items that overlapped for BIGL12 and BIGL22. The lucky and unlucky questions simply asked: "How lucky do you feel right now?" and "How unlucky do you feel right now?" The two response scales were five-point Likert with the following anchors: not at all (un)lucky; a little (un)lucky; (un)lucky; quite (un)lucky; very (un)lucky. Table 5.1 provides labels, descriptions and item content for constructs and variables used in the analyses below.

5.2.3 The Game

The game was played between two participants and involved the roll of a dice. I ran a pilot study with approximately 100 subjects refining these game features and other aspects of the study. I tried a few variations of instructions and solicited feedback about the experience of participants in that pilot and finally settled on the study as described here. The final version of instructions and a description of game play are provided below.

5.2.3.1 Game Instructions and Protocol

Upon completing the initial surveys, participants saw a screen that said in large bold letters, 'Please ask the experimenter what to do next.' This page was also brightly coloured so the experimenter could see at a glance when participants had reached the end of the surveys. The instructions, delivered verbally, then began. (In the text below, spoken instructions are in bold font and comments to the reader are in normal font.)

> **Okay, it looks like everyone is finished with the initial surveys. Everyone please stand up and come over to the table to face me.**
>
> Participants then approached a large table to one end of the lab.
>
> **Now you're going to play a game against one of your fellow students. I'll explain what's a stake in a moment, but first I'll tell you how the game is played. First, each of you will pair with another participant.**
>
> At this point I would allocate participants to dyads. Computers in the lab were numbered from one to six. The person at computer one would play the person at computer two, three would play four, and five would play six. Participants at the

Construct	Construct Label	Indicator Label	Indicator Content
General Belief in Luck	**GBL**	GBL_01	Luck plays an important part in everyone's life.
		GBL_02	I believe in luck.
		GBL_03	There is such a thing as good luck that favors some people, but not others.
		GBL_04	There is such a thing as bad luck that affects some people more than others.
Personal Good Luck	**PGL**	PGL_01	I consistently have good luck.
		PGL_02	Even the things I can't control tend to go my way because I'm lucky.
		PGL_03	Luck works in my favour.
		PGL_04	I consider myself to be a lucky person.
		PGL_05	I often feel like it's my lucky day.
Personal Bad Luck	**PBL**	PBL_01	I consistently have bad luck.
		PBL_02	Even the things in life I can control don't tend to go my way because I'm unlucky.
		PBL_03	Luck works against me.
		PBL_04	I consider myself to be an unlucky person.
		PBL_05	I often feel like it's my unlucky day.
Lucky Now	**LN**	LN1	How lucky do you feel right now?
Unlucky Now	**ULN**	ULN1	How unlucky do you feel right now?

Table 5.1: Predictor Variable Labels and Content - Labels and content for predictor variables used in the analyses in this chapter. Construct (scale) labels and descriptions for a given set of items are in bold.

odd numbered computers would be assigned the role of Player One, while those at the even numbered computers would be assigned to the role of Player Two[1].

Then, you must each select a number from one to six. It can be the same or different from your competitor. Please tell me your chosen number.

I would then ask each participant for his or her chosen number, and write this down on a formatted sheet of paper in front of me.

Player One will roll the dice first, with the objective of rolling his or her chosen number in the fewest rolls possible. Having rolled his or her chosen number, I will then write down the number of rolls. Player Two will then try to beat Player One, by rolling his or her chosen number in fewer rolls. In the event of a tie, there will be a sudden-death roll-off, won by the player rolling the highest number. Each roll of the dice must land inside this box or it does not count. Please choose any of the dice on the table.

Each participant would choose a single dice. I then asked each participant if the instructions so far were clearly understood, answer any questions, or briefly restate the instructions if it appeared there was any misunderstanding. I kept an open-topped box, approximately 20 x 30 cm on the table, and had a selection of different coloured dice for participants to chose from.

Now I'll explain the prize for winning the game. The winner of the game will get to leave the study early. You've signed up for a one hour study. You've now been here for about 10 minutes. If you win, you'll go back to your computer to answer about five minutes more of questions, and then after you're finished with those, you are free to go. However, if you lose, after you finish the rest of this study, you will be required to stay on to the end of the hour to complete a second, unrelated study.

I would then show the participants green and red slips of paper that would be awarded to the winner and loser respectively.

So that there is no misunderstanding later of who gets to go early and who has to stay, I will award the winners a green slip of paper, and the losers will get a red slip of paper. At the conclusion of the first study, if you have a green slip of paper, just show that to me, and you can go. If you have a red slip of paper, when you finish this study and show me your slip of paper, I'll log you into the second study.

I then briefly described the second unrelated study as a monotonous study on guessing. I again asked if there were any questions, and briefly restated the rules and the stakes involved in the game.

Okay, let's start! Rolling for a ___!

[1]Below I report on tests of differences in dependent variables that result from Player One rolling first and Player Two rolling second.

> Player One then rolled the dice until his or her number landed face up. After each roll, I would state a quick summary in the style of a commentator: "…three rolls, looking for a six!…four rolls, looking for a six.…FIVE ROLLS GETS A SIX!" I would then turn to Player Two, and ask: "Do you think you can beat that?" After his or her reply, they would begin rolling and I would provide running commentary as before.

Participants waiting to play watched on until it was their turn. When participants finished playing the game, they were provided either a red or green slip of paper, and asked to return to their computer to complete the rest of the study.

When the study was complete, win-outcome participants were debriefed and allowed to leave. Loss-outcome participants were logged into the next study that ran until the end of the hour, they were then debriefed on both studies and allowed to leave.

5.2.3.2 Game Features

There were several features designed into the game that I call attention to.

The game outcome was transparently uncontrolled by the experimenter. The game had no deception or control by the experimenter, and this was very clear to participants. Participants were undergraduate psychology students and had been taught about classic social psychology experiments involving deception. They have been known to be suspicious that games played on a computer may have pre-determined outcomes.

The game outcome had natural variation in closeness. Based on probability, the game outcomes tended to cluster toward being closer, but overall created a dataset that provided a distribution to allow for examination of the counterfactual closeness hypothesis. As a demonstration of this, I calculated the rolls differences $= |Rolls_{player\ 1} - Rolls_{player\ 2}|$ for each dyad and checked the frequencies. There were 9 ties (with a roll-off), then the count of dyads with a rolls difference from 1 to 12 were: 18, 7, 8, 14, 4, 7, 4, 2, 3, 2, 4, and 3. There were also two dyads with a rolls difference of 14 and two dyads with a rolls difference of 18.

The game outcome was real and immediate. Providing monetary pay-offs to participants might have been preferable, but it is highly unlikely that I would have been able to procure the funds or ethics approval to pay winning players. So instead, I used the only other currency at I had available to me: study participation credits. Students in the subject pool were awarded credit points toward their final grade for participating in studies[1]. So in effect, I was awarding winners with a 1/2 credit. Wieth & Burns (2006) used a similar manipulation in a study on problem-solving. Participants in their studies exhibited increased recall memory, and problem solving performance when incentivised with the opportunity to leave the experiment early. Winning participants received a green slip paper, and losing participants received a red slip. The slips of paper were usually placed just beside participants' keyboard or mouse when they returned to their computers. These slips of paper helped to ensure I did not mistakenly allow a loser to leave early, as well as to provide a constant reminder to the participants of the game outcome.

5.3 Dependent Variables

Having finished the game, participants were asked to return to their seats with their (red or green) slips of paper and instructed to scroll down to find the advance page button. Having continued, participants saw a screen that asked them to record whether they won or lost the game, their chosen number, how many rolls it took to get that number, and how many rolls is took their competitor to get his or her chosen number. These responses were used as a manipulation check. Participants' recollection of the game outcome and number of rolls universally agreed with my lab notes taken at the time of game play.

Participants then answered questions relating to: 1) lucky and unlucky feelings, both personally and an estimate of the opponent; 2) perceptions of the game and its outcome; and 3) risky choice questions, a selection of which estimates of the opponent's responses were also elicited. These items are described below and Table 5.2 provides labels and descriptions for constructs and variables used in the analyses below. The first block of Table 5.2 provides measures related to lucky and unlucky feelings. Measures

[1]Students were limited to a maximum of four credits, which were provided on the basis of one hour earning one credit.

Description	**Item Label**	
	Self	**Opponent**
Lucky Now, Time 2	LN2_me	LN2_opp
Unlucky Now, Time 2	ULN2_me	ULN2_opp
Change in Lucky Now, LN2 - LN1	Shift_LN	—
Change in Unlucky Now, ULN2 - ULN1	Shift_ULN	—
Subjective Closeness	Closeness	—
Rolls Difference	RD	—
Adjusted Rolls Difference	RD3	—
Skill Attribution	Skill	—
Chance Attribution	Chance	—
Luck Attribution	Luck	—
Dice Game, Minutes Gambled	DG_Mins_me	DG_Mins_opp
Dice Game, Gamble Confidence	DG_Conf_me	DG_Conf_opp
Coin Game, Minutes Gambled	CG_Mins_me	CG_Mins_opp
Coin Game, Gamble Confidence	CG_Conf_me	CG_Conf_opp
Lottery	Lottery	—
Vaccine	Vac	—
Balls_1	B1	—
Balls_2	B2	—
Balls_3	B3	—

Table 5.2: Descriptions and Labels for Dependent Variables - For select variables a participant's estimate of the opponent's response has been elicited. These are indicated in table, where the item label has been appended with '_opp'.

in the second block are related to perceptions of the game and game outcome. The third block contains the risky choice dependent variables.

Recall that a participant allocated to be Player One always rolled first, and a participant allocated to be Player Two always rolled second. I was concerned that, despite game outcome being randomly controlled for with respect to player role allocation to, this might have introduced a systematic bias to the dependent variables. Player One and Player Two may have been experiencing the game in fundamentally different ways. I looked at all possible dependent variables in the study and conducted approximately 20 t-tests for mean differences by Player One versus Player Two. The lowest significant p-value returned was 0.13, indicating that there were no differences between rolling first or second.

5.3.1 Lucky and Unlucky Feelings

Participants were asked again how lucky and unlucky they felt at that present moment in the same format as the pre-manipulation survey. An additional two questions were present however: "How lucky do you think your opponent feels right now?" and "How unlucky do you think your opponent feels right now?" The response format was the same as the first two questions.

5.3.2 Closeness

As a measure of counterfactual closeness, participants were asked how close the game was. They were provided the following text and a text box for their response.

> Often people will say that a game was "close", or a "close call", meaning that one person only barely beat the other person. We are interested in finding out your impressions of closeness in the dice game you just played.
>
> Please indicate how 'close' you think the game you played was, regardless of who won or lost. That is, the game was close if you won or lost by a small margin, and the game wasn't close if you won or lost by a large margin. Enter a number from 0 to 100. 0 = not close at all; 100 = very very close.

So, the variable Closeness was a subjective measure of game closeness that could differ between two participants who were party to the same game. The value of Closeness could range from zero to 100, with 100 being a game judged by a participant to be very close.

5.3.3 Rolls Difference and Adjusted Rolls Difference

I wanted an alternate measure of closeness that was objective. So I calculated a variable I called RD, using only the number of rolls of two players. It is actually a measure of rolls difference, where a lower value for RD indicates a closer game. The variable was calculated as: $RD = |Rolls_{me} - Rolls_{opp}|$, where $Rolls_{me}$ is the number of rolls of a focal player, $Rolls_{opp}$ is the number of rolls for his or her opponent.

I wanted an alternate measure of closeness that was objective and also adjusted for the total number of rolls. So I calculated a variable I called RD3, again using the number of rolls of two players. This is also a measure of rolls difference, but is adjusted for the total number of rolls. The variable was calculated as: $RD3 = \frac{|Rolls_{me} - Rolls_{opp}|}{Rolls_{me} + Rolls_{opp}}$, using the same notation as previously. The difference between two players rolls was divided by the total number of rolls, so a lower value for RD3 indicates a closer game. For both RD and RD3, the measure would be equal for both players party to the same game.

As an example of how this adjustment worked across a range of game outcomes, a game outcome of 1 versus 3 yields an RD3 of 0.50. Other game outcomes yielding an equivalent RD3 would be 2 versus 6, and 3 versus 9. For games where outcomes were very close, but the number of total rolls was low (say of a game outcome of 1 versus 2), RD3 was greater than that of for a game with the same number of rolls difference, but greater total rolls (say a game outcome of 7 versus 8). In this example, the first outcome RD3 is 0.33, and the RD3 in the second outcome is 0.07.

5.3.4 Attribution to Skill, Chance and Luck

I wanted a measure of the attribution of the game outcome to skill, chance and luck. Attributions to luck should be associated with belief in luck, and these attributions are one of the earliest measures in the study of perceptions of luck with the finding that chance and luck are conceived as different causal explanations (Keren & Wagenaar, 1985; Wagenaar & Keren, 1988). Measuring these attributions allows for a replication of early findings. It also allows for an examination of the impact of luck beliefs on perceptions of causal forces giving rise to a game outcome. So next I asked participants to “Please indicate how much you think the dice game you played earlier involved skill, chance, and luck. The total should equal 100.” I provided text boxes for each of skill, chance and luck that indicated a % to the right of the box. At the bottom was a box for the total so subjects would restrict their responses for skill, chance and luck to some combination of 100.

5.3.5 Dice Game Gamble

The first page required responses to four different questions, and had a bolded large-font header that said, “A Gamble with your time?”, continuing with the following text:

> You're probably aware that 5% of the final grade for Psychology 1001 students at the University of Sydney is based on completing 4 experiment credits. You have been given 1 credit for the experiment you are doing now, regardless of whether you're going home early or staying through to the end of the hour.
>
> Assume you have 1 more credit (a one hour experiment) to do before you finish your course requirements, and that right now you could make a gamble with the amount of time you would be required to do for that credit.
>
> The table below shows different payoffs for different amount (minutes) gambles:

I then provided a table each for the winning and losing consequences for each 10-minute increment gamble of time, starting with zero and going to 60. For each minute gambled, a winning outcome resulted in one minute less of experiment a person would have to do to get the remaining credit. However, for each minute gambled, a losing outcome resulted in two minutes more of experiment a person would have to do to get the remaining credit.

There were two tables, with two columns each. For the table on the left side of the page, the first column of the table read, "If you gamble this many minutes. . . ", and then listed in rows, 60, 50, 40, 30, 20, 10, 0. The second column read ". . . and WIN, then you would have to do this many more minutes to get you 1 hour credit." Then listed in rows were, 0, 10, 20, 30, 40, 50, 60. For the table on the right, the first column was equivalent to the table on the left. The second column of the right-hand table read, ". . . and LOSE, then you would have to do this many more minutes to get your 1 hour credit." Then listed in rows were, 120, 110, 100, 90, 80, 70, 60.

I then asked "How much time (in minutes) would you gamble? (You could gamble any number of minutes from 0 to 60.)" A text box was provided for their answer. Below this question was another question about confidence. It read: "Sometimes, people have a special feeling about whether they might win or lose. How confident (from 0 to 100) are you that you would win this gamble? 0 = not confident at all; 100 = very very confident.", and a text box was provided for their response.

A final two questions mirrored these time gamble and confidence questions, but asked about the participant's competitor and read: "How much time (in minutes) do you think the person you played the dice game against (at the beginning of the experiment) would gamble?"; "How confident (from 0 to 100) do you think the person you played the dice game against (at the beginning of the experiment) would be to win this gamble? 0 = not confident at all; 100 = very very confident."

5.3.6 Coin Game Gamble

The next page was very similar as before, but slightly altered the paradigm. The page header read, "A Coin Toss Game". This was followed, "Imagine a game similar in every way to the dice game you played before, except instead of using dice, you use a coin toss. Thus, instead of picking a number, you would pick either heads or tails and toss the coin until your choice came up. Whoever got their chosen coin side first would be the winner. Now, as before assume that you have 1 more credit. . . " From that point forward the text and questions were the same as the previous page.

5.3.7 Lottery Gamble

The page containing this question had the header in bold: "A Special Lottery". The text read as follows:

> Imagine a lottery where the number of tickets is strictly limited to 100. One and only one of those tickets will pay the winner exactly 100 times the amount he or she pays for a ticket. So, for example, if you paid 5 cents for a ticket, and you won, you would get 5 dollars. If you paid 1,000 dollars for a ticket you won, you would get 100,000 dollars. You can buy only one ticket.
>
> On average, people spend about 5 dollars on a ticket.
> **How much do you think you would spend?**

The response format was a 7-point scale with the following anchors, A lot less than 5 dollars, Less than 5 dollars, A little less than 5 dollars, About 5 dollars, A little more than 5 dollars, More than 5 dollars, A lot more than 5 dollars. Pre-testing had shown that the response format, when left open-ended, had resulted in large outliers. I attempted to correct this by both limiting responses, and providing an 'average' amount most people spent.

5.3.8 Vaccine

The page containing this question had the header in bold: "Flu Season". The item read as follows:

> There is a very nasty flu going around. Fortunately, there is a vaccine which works against this flu, but it causes sickness immediately after vaccination. If you take the vaccination you'll be sick for a couple of days - probably still able to work or

> attend university classes. However, you can be sure that if you come into contact with the virus, you won't get the flu. If you don't take the vaccination and you don't come into contact with the virus, you won't be sick at all. However, if you don't get the vaccination and you do come into contact with the virus, you'll be very sick 4 or 5 days - in bed most of the 4 or 5 days.
>
> **How likely are you to take the vaccine?**

The response format was on a 4-point scale with the anchors of Very Unlikely, Unlikely, Likely, and Very Likely.

5.3.9 Balls Gamble 1

There were three questions of the balls-in-an-urn tradition. The first one read 'A Ball Game' across the top of the page in bold font. Below read:

> A box is filled with 500 GREEN balls, and 10 RED balls. Imagine a game where, for each GREEN ball you draw, you will be paid 25 cents. However, if you draw a RED ball, you will lose all the money you won, and the game will end. You must decide in advance how many balls you will draw from the box.
>
> **How many balls will you draw from the box?**

A response field was presented, and to the right of the box was the word 'balls'.

5.3.10 Balls Gamble 2

The next balls page was headed by 'Another Ball Game', and the text below it read:

> In this game, you would be paid 20 dollars for getting a green ball and 0 dollars for getting a red ball. Box A is filled with 80 GREEN balls, and 80 RED balls. Box B is filled with GREEN balls and RED balls, but you don't know how many of each. (Your chances of winning with Box B could be the same, better, or worse than your chances with Box A.)
>
> **Which box would you choose from?**

Two radio buttons were provided, one above each of the two options, Box A and Box B.

5.3.11 Balls Gamble 3

This last page was headed by 'One More Ball Game', and below that read:

> In this game, you would be paid according to the following: For a red ball, you will be paid nothing. For green ball, you will be paid 50 dollars. For a yellow ball, you will be paid 100 dollars. Box A is filled with 100 GREEN balls, and no other balls. If you draw from this box, you can be certain you will get a green ball. Box B is filled with 50 RED balls and 50 YELLOW balls. If you draw from this box, you will have a 50/50 chance of getting a yellow ball, and a 50/50 chance of getting a red ball.
>
> **Which box would you choose from?**

Two radio buttons were provided, one above each of the two options, Box A and Box B.

5.3.12 Features of the Dependent Variables

There were several features designed into the collection of dependent variables.

The dependent variables were completed quickly. The most important aspect I considered when designing these measures was that of brevity. The pilot study had indicated a relative ease of influencing lucky feelings, and contrary difficulty of influencing risky choice variables to a meaningful extent. I thought that perhaps the effect of the manipulations might quickly extinguish. Thus I decided to restrict the dependent variables to only a few. The dice game gamble was designed to hold the game paradigm exactly constant, thereby reducing cognitive load as much as possible. For the Dice Gamble and Coin Gamble I included a table of the payoffs of different gambles so that participants would not have to do any calculation, and could understand the consequences as easily as possible.

A measure of counterfactual closeness is prioritised. Following the game, the first measure was closeness. Again reflecting the prominence of the counterfactual closeness hypothesis, I wanted to ensure that the subjective measure of closeness was not impacted by asking about lucky or unlucky feelings first.

A measure of both lucky *and* unlucky feelings was included. It was important to maintain measures of a respondent's lucky and unlucky feelings as close to the game outcome as possible, in order to establish precedence over risky choice dependent variables. I included unlucky feelings in this study for two reasons. The first reason was to parallel the PBL construct. By including the dimension of bad luck in a scale measuring beliefs in luck, the question of the relation of feeling lucky to feeling unlucky is obviously raised. A number of analyses below will address the question of the relationship of feeling lucky to that of feeling unlucky, as well as differential prediction of these two measures for various dependent variables.

Dependent variables had correspondence with the context of the manipulation. By using time, I have explicitly drawn on the same 'good' that was at stake in the actual game the participants played. In so doing, I've attempted to maintain a consistency between the actual consequences of winning and losing, and the hypothetical consequences of the gamble opportunity of participants. I asked about the confidence of the dice game gamble in order to take a second measure of the influence of the game outcome on risky choice, potentially linking results from this study to those reported in Chapter 4.

Risky choices were sampled from different domains. Continuing the theme of degrading similarity from the original context, the lottery gamble represented a departure from the type of stake involved—from time to money. Pilot testing of a similar question had shown that an open-ended response format would result in a non-normal distribution with extreme outliers. Thus, I used an ipsative format, and provided an anchor of sorts—the average amount gambled. I wanted a gamble that held the odds of winning constant, but increased the amount won for an increasing amount of the gamble. By limiting the number of tickets to 100, the probability of winning could be held constant, and was easily intuited by participants. But by allowing a leveraging of the amount paid for the ticket, the amount of the pay-off could vary.

The Vaccine question was the least similar of all question contexts. It involved no numerical probabilities, and contained no explicit statement of financial reward. It was therefore somewhat 'qualitative' as compared to the other questions, for which probabilities could be calculated based on numerical information provided. I included three additional risky choice measures: Balls Gamble 1 (Balls_1), Balls Gamble 1 (Balls_2), and Balls Gamble 1 (Balls_3). The first balls question is similar to the lottery gamble question. The probabilities of win or loss can be calculated, or at least intuited, in advance. However, unlike the lottery question, each incremental level of gamble inheres an additional unit of risk, while the potential pay-off also increases. I intended the question to trigger respondents to think in a 'pressing your luck' manner. That is, how many draws would a participant be willing to take in the face of what is eventually a certain loss of the entire winnings.

The last two balls questions differed from other questions in two important ways. Firstly, the response format was dichotomous. Secondly, the questions address ambiguity tolerance rather than risk-tolerance per se. The choices were about known versus unknown probabilities with the expected pay-offs held constant. I anticipated that participants who felt lucky would be more likely to have an optimism bias toward the boxes of unknown probabilities.

5.3.13 Terminology: Luck Feelings, Luck Beliefs, and Congruence

I conclude the method section with a final comment regarding the terminology I will use to discuss the luck belief and luck feeling variables above. There is scope for confusion when discussing the two types of luck feelings and the two personal luck beliefs. I describe a convention now, which will attempt to lend clarity to the discussion of analyses and results below.

Given that I will be discussing both *lucky* feelings and *unlucky* feelings, a general term that includes both of these feelings is needed. The question, "Do lucky feelings influence choice involving risk?" could be read as either "Do (both) lucky and unlucky feelings influence choice involving risk?", or it could be read as "Do lucky feelings (but not unlucky feelings) influence choice involving risk?" I reserve the term "luck feeling(s)" to be inclusive of both lucky *and* unlucky feelings. A "lucky feeling" and an "unlucky feeling" is therefore reserved for the specific sense, meaning one and not the other.

A second term that should prove useful is to refer to belief in personal good luck (PGL) and belief in personal bad luck (PBL), as the "personal luck beliefs", in contrast to the general belief in luck (GBL). I primarily examined the personal luck beliefs in the analyses, with limited treatment of the general belief in luck.

Finally, I will use the term "congruent" quite extensively throughout the remainder of this chapter. Foreshadowing results to come, the concept of congruence will serve to explain the relation of game outcome to luck feeling. The "outcome congruent luck feeling" for win-outcome participants is a lucky feeling; for loss-outcome participants it is an unlucky feeling. This relation can then be used to express a prediction. For example, "the outcome congruent luck feelings are expected to be better predictors of risky choice, relative to outcome non-congruent luck feelings." This is a succinct way of saying, "the lucky feelings of win-outcome participants and unlucky feelings of loss-outcome participants are expected to be better predictors of risky choice, relative to (respectively) the unlucky feelings of win-outcome participants and lucky feelings of loss-outcome participants."

Congruence can also relate an outcome and a personal luck belief. A belief in personal good luck (PGL) is congruent with a win-outcome, whereas a belief in personal bad luck (PBL) is congruent with a loss-outcome. It is therefore possible to describe the general relation of outcome congruent luck belief and outcome congruent luck feeling. For example, "the outcome-congruent personal luck belief is expected to predict the outcome congruent luck feeling" expresses two predictions in a single statement: one for win-outcome participants (PGL is expected to predict lucky feelings); and one for loss-outcome participants (PBL is expected to predict unlucky feelings).

In summary, I introduce 'luck feeling(s)' as a general term that includes both lucky and unlucky feelings. I introduce 'personal luck belief(s)' as a general term that includes both PGL and PBL. And finally, I introduce the concepts of 'outcome congruent luck feeling' and 'outcome congruent personal luck belief'. The former relates a win-outcome and loss-outcome to lucky and unlucky feelings respectively. The later relates a win-outcome and loss-outcome to PGL and PBL respectively.

5.4 Preliminary Analyses

Results are presented in three different sections below: 1) preliminary analyses are presented in this section; 2) Section 5.5 presents analyses of main effects of game outcome, closeness, and luck beliefs on luck feelings and risky choice; and 3) 5.6 presents PLS analyses of the general model described in the opening paragraphs, splitting the sample by game outcome.

The preliminary analyses begin with an examination of the inter-relationships of three game closeness measures: subjective closeness (Closeness), rolls difference (RD), and rolls difference adjusted for total number of rolls (RD3). The next preliminary analysis examines attributions of the game outcome to skill, luck and chance. The final preliminary analysis examines the relationship of luck beliefs and Closeness.

5.4.1 Closeness Measures Compared: Closeness vs. RD and RD3

Although the subjective closeness (Closeness) and the rolls difference measures (RD and RD3) should covary, they are not identical and may not explain the same—or the same amount of—variance in dependent variables. The correlation of Closeness and RD was quite strong but doesn't indicate unity, $r(177)$ = -0.63, $p < .001$. Closeness and RD3 are similarly correlated, $r(177)$ = -0.69, $p < .001$. The negative correlations are due to the rolls difference measures (RD and RD3) implying the inverse of closeness: the smaller the difference in rolls, the 'closer' the game should be viewed.

It is possible that Closeness has a non-linear relationship with either of the objective measures of closeness (RD and RD3). Perhaps participant views of closeness are such that closeness perceptions quickly diminish with increasing rolls difference, and then flatten out. To test for this, I graphed the relationship between Closeness and the absolute value of rolls difference, RD; and between Closeness and the absolute value of adjusted rolls difference, RD3. Figures 5.1 and 5.2 present these graphs. I use only data from dyads with an absolute rolls difference of less than 8. This range of 1 to 7 accounts for over 80% of the data. The remaining 20% of the data was distributed sparsely across absolute rolls differences that range from 8 to 18 and thus have an undue influence on the line of fit. For each graph, I have fitted two lines to the data. The straight line is the linear relationship, and the slightly curved line is a fourth order polynomial relationship.

With greater free parameters, the polynomial function should fit to the data better (deviating from a straight line) if there was in fact a non-linear relationship. In both graphs, but especially for RD3, there is very little difference between the linear function and the polynomial. Second and third order polynomials were also plotted, and they were very similar to the fourth order polynomial. From this I concluded that (subjective) Closeness and the two objective measures of closeness are linearly related to a

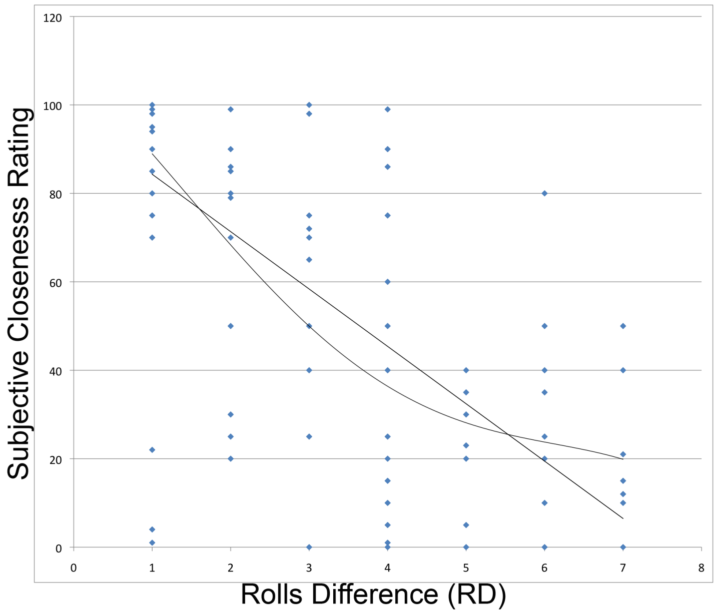

Figure 5.1: Closeness Compared to RD - A graph of two lines of fit for the relationship of subjective closeness (Closeness) and absolute rolls difference (RD). The straight line is the linear relationship, and the curved line is a fourth order polynomial relationship.

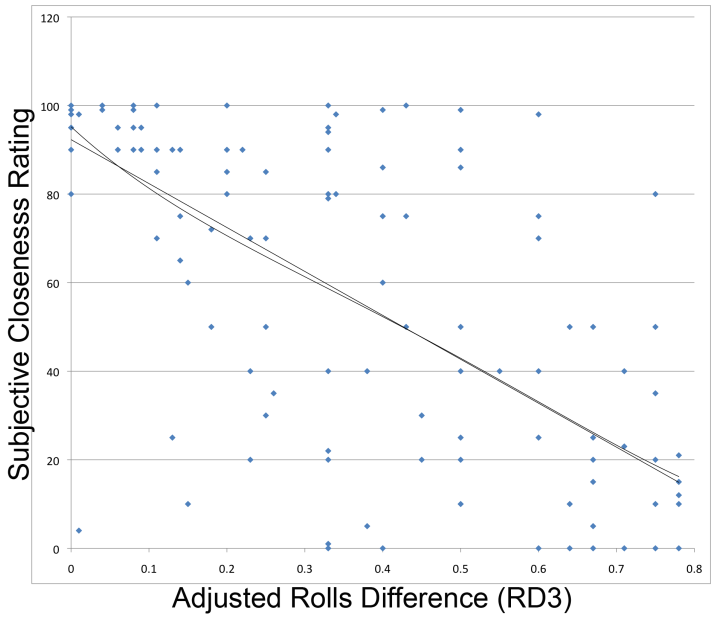

Figure 5.2: Closeness Compared to RD3 - A graph of two lines of fit for the relationship of subjective closeness (Closeness) and adjusted absolute rolls difference (RD3). Again, the straight line is the linear relationship, and the curved line is a fourth order polynomial relationship.

sufficient extent that non-linearities in Closeness do not pose a threat to any analyses below.

An equivalent approach was taken, separately for win- and loss-outcome participants, to examine the linearity of the relationship between Closeness and both post-game luck feeling. Thus, a total of four graphs were created. All four graphs were similar to those in Figures 5.1 and 5.2; visual inspection indicated no or only very slight non-linear relationships.

This lends confidence to the use of the Closeness measure, but does not conclude which of the three measures (Closeness, RD and RD3) will be the best predictor of luck feelings. Results presented in Table 5.6 and associated discussion will address that question momentarily.

5.4.2 Game Outcome Attributions: Skill, Luck and Chance

To what extent were skill, luck and chance perceived to play a role in the game? How were they related to one another, and to other variables in the study? Table 5.3 reports by game outcome, the correlations of skill, luck and chance with other study variables. As can be seen, the inter-correlations of skill, luck and chance do not differ by game outcome. Luck and chance are nearly unitary opposites with a correlation of -0.91 for losers and -0.90 for winners ($ps < .001$). Interestingly though, skill and chance are negatively correlated at -0.42 for losers and -0.47 for winners ($ps < .001$), although luck and skill are not. For losers the luck - skill correlation was $r(89) = 0.01$ ($p = .928$). For winners the luck - skill correlation was $r(88) = 0.03$ ($p = .781$).

Luck and chance have a very similar pattern of correlation across other study variables, while skill was uncorrelated with any other variable, except chance. I note that none of the attributions are correlated with closeness or adjusted rolls difference, RD3. Skill, luck and chance are uncorrelated with any of the dependent variables of the study, except for Balls_3, which registers a positive correlation with skill, a negative one with chance, and no correlation with luck. This is a subtle yet interesting pattern that deserves a little more comment. Attributions of luck and chance are negatively correlated very highly at around -0.90: nearly (inversely) unitary after taking error into account. However, looking at attribution to skill, *only* attribution to chance has a statistically significant correlation. Unfortunately, Keren & Wagenaar (1985); Wagenaar & Keren (1988) did not report correlations of skill, luck and chance attributions, so these results

	Loss-Outcome Participants			Win-Outcome Participants		
	Skill	Luck	Chance	Skill	Luck	Chance
Skill	–	–	-0.42	–	–	-0.47
Luck	–	–	-0.91	–	–	-0.90
Chance	-0.42	-0.91	–	-0.47	-0.90	–
Closeness	–	–	–	–	–	–
RD3	–	–	–	–	–	–
GBL	–	0.58	-0.49	–	0.54	-0.50
PGL	–	0.42	-0.36	–	0.43	-0.40
PBL	–	0.40	-0.32	–	0.39	-0.41
LN2	–	–	–	–	0.65	-0.59
ULN2	–	0.36	-0.28	–	–	–
DG_mins	–	–	–	–	–	–
DG_conf	–	–	–	–	–	–
CG_mins	–	–	–	–	–	–
CG_conf	–	–	–	–	–	–
LG	–	–	–	–	–	–
Vac	–	–	–	–	–	–
Balls_1	–	–	–	–	–	–
Balls_2	–	–	–	–	–	–
Balls_3	0.33	–	-0.26	0.24	–	-0.27

Table 5.3: Game Attributions Correlated With Study Variables - Correlations of Skill, Luck and Chance attributions with other study variables. The matrix to the left is for losers, the matrix to the right is for winners. Reported correlations are significant at $p < .05$.

cannot be compared to theirs. However, this pattern has been observed repeatedly in (other, unreported) data from my lab, so this seems to be a robust phenomenon. Perhaps this argues that luck and chance are substitutes for one another, depending on the strength of luck beliefs, but skill and luck are seen as distinct for everyone? In other words, luck attributions are a proxy for luck beliefs.

Some support for that view can be found in the lack of correlation of skill with any luck belief, but similar magnitude correlations for the three luck beliefs with attributions to luck and chance. The three dimensions of belief in luck correlate in the same direction, and nearly the same magnitude for luck and chance across game outcome. Luck attribution was positively correlated with beliefs in luck, GBL, PGL, and PBL. Chance attribution was negatively correlated with these. The three attribution means for two groups formed by a median-split of GBL help clarify the correlations. Skill attributions means were 4.59 and 5.61 for the low- and high-GBL groups respectively. Luck attribution means were 6.86 and 33.02; chance attribution means were 88.55 and 61.37. There were however fairly high standard deviations: 11.10 and 12.4 for skill attributions means for the low- and high-GBL groups respectively. Luck attribution standard deviations were 14.08 and 26.00; chance attribution standard deviations were 18.77 and 28.19. The group mean differences for both luck and chance attributions were statistically significant using an ANOVA test [respectively, F (1, 175) = 68.606; = 56.632, $ps < .001$]. The group mean difference for chance attribution was not [F (1, 175) = 0.337 $p = .562$].

Luck attribution has an interesting, albeit unsurprising, interaction across game outcome, with lucky and unlucky feelings. For losers, attribution to luck was positively correlated with unlucky feelings, and not lucky feelings. For winners attribution to luck was positively correlated with lucky feelings, and not unlucky feelings. As before, chance attribution has the opposite pattern to luck attribution. These correlations are outcome-congruent: lucky feelings among winners are correlated with luck attributions, whereas unlucky feelings among losers are correlated with luck attributions. Note that unlucky feelings appears to be considerably less coupled with luck attributions (0.36 for losers) than are lucky feelings (0.65 for winners). In PLS models to come, this outcome-congruent luck feeling response will become more clear.

A broad interpretation of these correlations indicates that luck attributions are associated with beliefs in luck, and with lucky (and unlucky) feelings taking into account outcome, but that risky choice was not related with luck attributions. Furthermore, skill and luck attributions are not related, but luck are chance are nearly substitutes for one other.

5.4.3 Closeness and Luck Beliefs

Does belief in luck impact perceptions of counterfactual closeness? I posited that counterfactual closeness might be related to belief in luck because those who believe in luck might have a biased view of the game outcome, that belief in luck—in addition to changing the way an individual sees chance events—might also change the way an individual sees the relative outcomes of chance events. Specifically, I thought that belief in personal good luck (PGL) would bias an individual to see the outcome as closer, relative to someone with low PGL. One of the items in the PGL scale asked about participant views regarding whether 'things tend to go my way', which could potentially reflect a selective attention or biased interpretation of outcomes. Similarly, I thought that high PBL would bias an individual to see the outcome as less close, relative to someone with low PBL given the inverse item in the PBL scale. I didn't have a specific proposition regarding GBL and closeness.

One test is a simple correlation between closeness and each of the three belief in luck sub-scales: PGL, PBL and GBL. I used the mean of the items to create a single score for each of PGL, PBL and GBL. There were no significant correlations between closeness and the three belief in luck scores. I then ran two separate correlations—one for winners, and one for losers. Again, there were no significant differences. Across the 12 correlations tested, the lowest p-value obtained was 0.11.

Another test of the relationship of closeness and belief in luck is to ask: If a member of a dyad has a stronger belief in luck than his or her opponent, will that member rate the game outcome as being closer, relative to the opponent? This calls for a χ^2 test of the relative cell counts in a 2 by 2 matrix of Closeness (higher versus lower) and belief in luck (higher versus lower). Using Player One as the reference member for the dyad, I categorised each Player One as either higher or lower in his or her rating of Closeness, PGL, PBL, and GBL, relative to Player Two of the same dyad. So, there were a total of four new variables created, and there were three total χ^2 tests. There are different sample sizes for each of the three tests because of removal of dyads for whom there was a tie in the ratings of Closeness or the luck belief.

The percentage of Player One participants who were higher in Closeness than the opponent did not differ by being higher PGL than the opponent [χ^2 (1, n=72) = 0.91, $p = .34$]. The percentage of Player One participants who ranked higher in Closeness rating also did not differ by rank in PBL [χ^2 (1, n=72) = 0.48, $p = .49$]. The percentage of Player One participants who ranked higher in Closeness rating also did differ by rank in GBL [χ^2 (1, n=64) = 0.06, $p = .80$]. The data clearly do not support a conclusion that Closeness and any luck belief are related.

5.4.4 Summary Results

These preliminary results accomplished several practical outcomes that will be carried forward in the chapter. First, they established that the subjective measure of closeness was linearly related to the objective closeness measures, RD and RD3. Thus, subjective closeness could be compared side-by-side with these two objective measures as an antecedent of luck feelings.

Second, the preliminary analyses found that attributions of luck, skill and chance provided a manipulation check of sorts, demonstrating the game was viewed by some participants as inhering an element of luck. Luck attributions positively correlated with all luck beliefs, and with game congruent luck feelings. Absent that finding further analysis might be suspect. Luck attribution was highly negatively correlated with chance attribution, consistent with early findings by Wagenaar & Keren. That consistency lends further confidence to the experimental manipulation. Luck attribution was not associated with skill attribution, although skill and chance attributions were moderately negatively correlated. From these findings I suggest that luck and chance attributions are substitutes depending on luck belief.

Third, the preliminary analyses established that closeness perceptions were not associated with any luck belief, and that closeness was also not associated with game outcome. The results presented in Table 5.3 show that closeness was also not associated with attributions to luck, a proxy variable for luck beliefs, across game outcome. For these results, I am confident that the personal luck beliefs and game outcomes do not need to be taken into account as antecedent to closeness.

I now turn to tests for effects of the game outcome on luck feelings and risky choice, and include an interaction test of game outcome and closeness as an early test of the counterfactual closeness hypothesis.

5.5 Game Outcome, Closeness, and Luck Beliefs

5.5.1 Game Outcome

What effect did winning and losing have on luck feelings and risky choices? As a basic start to answering this question I considered conducting a series of independent samples t-tests where game outcome was the between subjects variable (i.e., winners and losers). Candidates for the test were 17 dependent variables, some of which factor together (i.e., DG_mins and CG_mins). For the sake of discussion, some further grouping of the variables is warranted. Two of the dependent variables can be grouped together as the *luck feelings* variables. These include lucky feelings (LN2) and unlucky feelings (ULN2). There are a total of seven risky choice variables, coded as higher rating being equivalent to greater risk-taking. Two of the risky choice variables can be grouped together as the *minutes gambled* variables: DG_mins and CG_mins. There were two *gamble confidence* variables: DG_conf and CG_conf. There were a further five *risky choice* variables: Vaccine, Lottery Gamble, Balls_1, Balls_2 and Balls_3. However, Balls_2 and Balls_3 had a dichotomous response format, so I will conduct a χ^2 test for these two. Finally, there were four variables that related to *perceptions of the game or outcome*: Closeness, and attributions to Skill, Luck, and Chance.

Prior to conducting the tests, I examined the histograms and descriptives of these variables as a check for normality, one of the assumptions of the independent samples t-test. None closely matched a normal distribution. Both DG_mins and CG_mins had peaks at zero, thirty and sixty. Together, these peaks accounted for 72.4% and 68.6% of subjects across the two measures respectively. With only a single exception of five, the remainder of responses were ten, twenty, thirty, forty, and fifty. Both confidence measures had very high model responses of 50% (44.4% and 59.0% of respondents for DG_conf and CG_conf respectively), and otherwise had a fairly flat distribution. Lottery Gamble had quite a normal distribution to the right of the median of four, but a flat distribution to the left of the median. Vaccine was skewed to the right, and Balls_1 was highly skewed to the left. Closeness appeared to have a U-shaped distribution with peaks at 0 and 100. Both Skill and Luck were skewed left, while Chance was skewed to the right.

Because of the questionable normality of many of the variables, I conducted a Mann-Whitney U test, which is a non-parametric alternative to the independent samples t-test. The results are presented in Table 5.4. Only the first two variables return a significant p-value. Those variables relate to luck feelings. All risky choices were not significantly different for winners and losers. Perceptions of closeness and attributions of game outcomes to skill, luck and chance were also not significantly different for winners and losers. A subsequent analysis using a traditional independent samples t-test did not yield appreciably different results. For example, the p-value for the mean difference of Loss- and Win-Outcome participants was 0.213 using the Mann-Whitney procedure, and 0.200 using the traditional test.

I ran a χ^2 test for the two dichotomous risky choice questions, Balls_2 and Balls_03. The percentage of participants responding to the riskier choice for Balls_2 did not differ by game outcome [χ^2 (1, N=178) = 0.52, $p = .59$]. This was also the case for Balls_3 [χ^2(1, N=178) = 1.31, $p = .34$].

The outcome of the game quite clearly impacted on both lucky and unlucky feelings, and in the congruent direction. There was an interaction pattern though, that is more clearly presented in graphical form in Figure 5.3. On average, winners felt more lucky than losers; and losers felt more *un*lucky than winners. The congruent luck feeling (i.e., lucky feelings of winners and unlucky feelings of losers) was about equal for winners and losers: winners reported a lucky feeling of 2.90 and losers reported an unlucky feeling of about the same amount, 2.66. The pattern was similar for the non-congruent luck feeling: Losers reported a lucky feeling of 1.52, while winners reported an unlucky feeling of about the same amount, 1.28. The absolute differences of LN2 and ULN2 across the two game outcome groups were about equal, 1.38.

Figure 5.4 shows the changes in lucky and unlucky feelings again by game outcome. Note that the magnitude of the change was much greater for outcome congruent luck feelings, relative to outcome non-congruent luck feelings. The impact of winning on moving lucky feelings upward was greater than the impact of losing on moving lucky feelings downward. The pattern was the same for unlucky feelings—the impact of losing on moving unlucky feelings upward was greater than the impact of winning on moving unlucky feelings downward. The mean differences by game outcome for the change in lucky and unlucky feelings were statistically significant as determined by an ANOVA test [respectively, F (1, 176) = 92.454; = 84.712, $ps < .001$]. This is further evidence that lucky feelings and unlucky feelings may be distinct from one another.

Variable	Group	Mean	SD	Min	Max	M-W U	Z	p
	Loss	1.52	0.77	1	4			
LN2	Win	2.90	1.10	1	5	1,237.5	-8.264	0.000
	Total	2.21	1.17	1	5			
	Loss	2.66	1.28	1	5			
ULN2	Win	1.28	0.58	1	4	1,389.5	-8.056	0.000
	Total	1.97	1.21	1	5			
	Loss	21.12	19.80	0	60			
DG_mins	Win	21.07	19.20	0	60	3,942.0	-0.056	0.956
	Total	21.10	19.44	0	60			
	Loss	28.15	20.92	0	60			
CG_mins	Win	26.18	20.53	0	60	3,746.0	-0.638	0.523
	Total	27.16	20.70	0	60			
	Loss	41.76	23.58	0	100			
DG_conf	Win	41.55	26.83	0	100	3,870.5	-0.275	0.784
	Total	41.66	25.18	0	100			
	Loss	49.66	20.40	0	100			
CG_conf	Win	46.17	23.62	0	100	3,614.0	-1.132	0.258
	Total	47.92	22.07	0	100			
	Loss	4.28	1.52	1	7			
LG	Win	4.40	1.61	1	7	3,770.5	-0.569	0.569
	Total	4.34	1.57	1	7			
	Loss	3.03	0.89	1	4			
Vac	Win	3.03	0.91	1	4	3,945.5	-0.046	0.963
	Total	3.03	0.90	1	4			
	Loss	72.79	108.84	1	510			
Balls_1	Win	80.78	114.01	0	510	3,792.5	-0.491	0.624
	Total	76.78	111.21	0	510			
	Loss	47.54	38.84	0	100			
Closeness	Win	54.76	34.94	0	100	3,533.5	-1.245	0.213
	Total	51.15	37.01	0	100			
	Loss	5.11	11.29	0	50			
Skill	Win	5.10	12.15	0	60	3,780.0	-0.646	0.518
	Total	5.11	11.70	0	60			
	Loss	19.55	25.28	0	90			
Luck	Win	20.72	24.13	0	82	3,679.5	-0.847	0.397
	Total	20.13	24.65	0	90			
	Loss	75.34	27.78	10	100			
Chance	Win	74.18	27.33	10	100	3,725.5	-0.703	0.482
	Total	74.76	27.49	10	100			

Table 5.4: Dependent Variable Means for Winners and Losers - Mann-Whitney test results show significant differences for only luck feelings variables. Risky choice measures are coded as higher rating being equivalent to greater risk-taking.

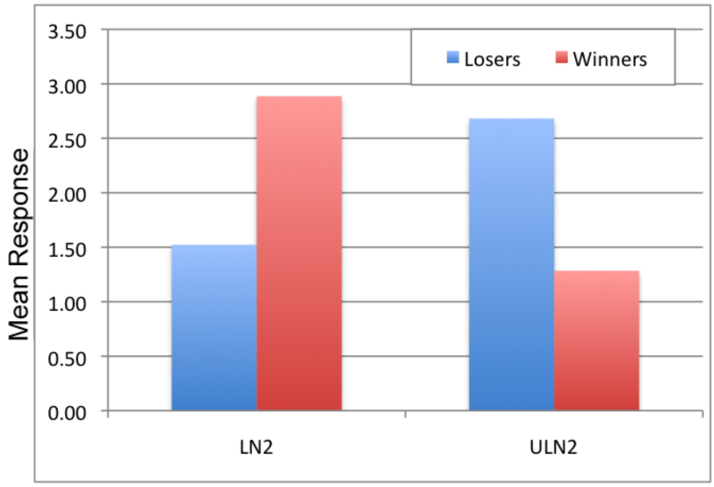

Figure 5.3: Lucky and Unlucky Feelings by Game Outcome - A graph of the average lucky feelings (LN2) and unlucky feelings (ULN2) for winners and losers.

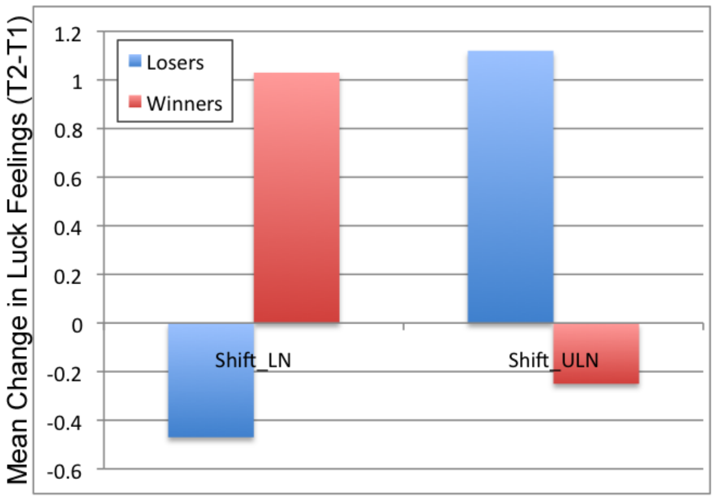

Figure 5.4: Changes in Lucky and Unlucky Feelings by Game Outcome - A graph of the average change in lucky feelings (Shift_LN = LN2 - LN1) and unlucky feelings (Shift_ULN = ULN2 - ULN1) for winners and losers.

Winning and losing had no effect whatsoever on any risky choice dependent variables. Examination of the means for winners and losers across a number of dependent variables in Table 5.4 makes this case clearly: On average, losers gambled 21 minutes in the dice game question, just as winners did. On average losers gambled 21 minutes on the coin game question, again, just as winners did. There were very slight differences in the dice and coin confidence, on average losers were about 3 points (out of 100) less confident than winners, for both questions. This same patterns continues for the remainder of the risky choices. I will explore moderators of the risky choice outcomes, including luck feelings and counterfactual closeness in sections to follow, but I am quite confident in asserting that game outcome has no direct or unique effect on risky choice.

I considered whether there might be differences between winners and losers on the subjective closeness measure, where losers would see the game as being closer than winners did for ego-defensive reasons. Winners, having won, might be less concerned with game closeness than losers. Upon losing, a person may knowingly or unknowingly distort their perception of closeness in order to feel more that they almost won. Perhaps though, this sort of perceptual distortion only exists for games where skill is a more prominent factor. There was no difference between winners and losers in their perceptions of game closeness. There was also no meaningful difference in the correlations of objective closeness to subjective closeness across winners and losers. For losers, the RD3-Closeness correlation was -0.68 and for winners it was -0.72 ($ps < .001$). Recall that RD3 was a measure of 'rolls difference' adjusted for total rolls, thus the negative correlation. For the unadjusted rolls difference (RD), the correlations were very similar by game outcome group. In the win-outcome group, the correlation of RD and Closeness was -0.650; for the loss-outcome group, the correlation was -0.619 ($ps < .001$). Again, a negative correlation results because rolls difference is inversely related to closeness. As the rolls difference increases, closeness decreases.

I also posited that, relative to losers, winners might see the game as inhering a greater degree of skill, and a lesser degree of chance and luck. This sort of effect would be in line with an illusion-of-control effect. However, there was no game outcome differences in the means of attributions to skill, luck and chance, as can be seen in Table 5.4.

5.5.2 Closeness

Recall that Chapter 4 found that closeness did explain additional variance beyond that of counterfactual direction alone. That finding called into question the counterfactual closeness hypothesis. However, a body of prior evidence from Teigen's studies supports the closeness hypothesis. Will closeness impact on luck feelings in this second study? Further tests of the interaction of outcome and closeness on luck feelings and risky choice will be presented momentarily. However, to first examine closeness as a main effect, I ran a correlation of closeness and the luck feelings measures (LN2, ULN2). The Closeness-LN2 correlation was 0.199, and the Closeness-ULN2 correlation was -0.192 ($ps < .01$).

What about closeness and risky choice? For this test, I ran a correlation of closeness and the risky choice measures (DG_mins, CG_mins, DG_conf, CG_conf, LG, Vac, Balls_1, Balls_2, and Balls_3). Of the risky choice variables, only Balls_1 was significant at 0.17 (n=177, $p = .03$), indicating that individuals who perceived the game as closer also chose to draw more balls. This however, is only one measure among many risky choice variables and the correlation is not large. It is therefore only limited support that closeness alone predicts risky choice. Again, further tests of the interaction of closeness and outcome are required before a definitive conclusion can be made.

The two rolls difference measures (RD and RD3) were uncorrelated with luck feelings and risky choice measures. So it is only the subjective perception of closeness that correlates with luck feelings, not the objective measures of measures. However, subjective perception of closeness did not correlate with luck beliefs or attribution of luck to the game outcome. The two patterns do not accord: why would closeness be related to luck feelings but not luck beliefs? To further investigate this question, the main effect of luck beliefs on luck feelings and risky choice will be investigated, and then later the interaction of closeness and luck beliefs.

5.5.3 Luck Beliefs

What impact do luck beliefs have on luck feelings and risky choice? Logically, a belief in personal good luck (PGL) should predict lucky feelings (LN2) and risky choice in a positive manner. But will a belief in personal bad luck (PBL) be associated with lower lucky feelings (LN2), or higher unlucky feelings (ULN2), or both? A further question in this theme is whether PBL will be associated with a reduction risky choice?

A first step in exploring these questions, I generated a correlation matrix for each of the personal luck belief subscales (PGL and PBL), created by averaging the constituent items) with the two luck feelings measures (LN2 and ULN2), and with the nine risky choice measures. That matrix is presented in Table 5.5. All three luck beliefs correlate positively with both LN2 and ULN2. I expected there to be congruence in the personal luck beliefs and luck feelings. That is, PGL would correlate with LN2; and PBL would correlate with ULN2. I was less certain about the correlation of GBL and the luck feelings measures, though I did anticipate they would be related positively because GBL is a strong predictor of PGL and PBL. However, I am somewhat surprised that PBL correlates positively with LN2 and that PGL correlates positively with ULN2. That is, I expected these two non-congruent belief-feelings pairings to be either unrelated or at least much less negatively correlated than they were within the congruent pairing. Look first to PBL and LN2, with a correlation of 0.28. The correlation of PBL and the congruent luck feeling LN2 is lower: 0.21.

Recall the 0.42 correlation of the two personal luck beliefs, PGL and PBL, which was reported in Chapter 3 (page 116). In the final model of that chapter, PBL and PBL were both positively predicted by GBL. Recall that PGL and PBL have the same antecedent (GBL) and that antecedent has about the same influence on both of these personal luck beliefs. Thus, if PGL is associated with lucky feelings, and PBL is associated with unlucky feelings, but PGL and PBL are correlated, then PBL could also have a positive association with lucky feelings. This is one possible explanation for these curious results; a spurious correlation.

The association of luck beliefs and risky choice was not nearly as strong. Both PGL and PBL correlated significantly with CG_Mins, and all three luck beliefs were associated with the lottery gamble response. Two further items correlated with PGL: CG_conf and Balls_3. Why would PBL be *positively* associated with risky choice? Perhaps this was artifactual, a consequence of PGL and PBL covarying with one another, and PGL being the stronger predictor of risky choice (as with LN2)? This is question can be more comprehensively addressed through the use of two separate PLS models of the system of variables; one for winners and one for losers. Without including game outcome and

	PGL	**PBL**	**GBL**	**LN2**	**ULN2**
PGL	1.00	0.52	0.73	0.36	0.22
PBL	0.52	1.00	0.57	0.28	0.21
GBL	0.73	0.57	1.00	0.33	0.19
LN2	0.36	0.28	0.33	1.00	-0.42
ULN2	0.22	0.21	0.19	-0.42	1.00
DG_mins	–	–	–	–	–
CG_mins	0.16	0.16	–	–	0.17
DG_conf	–	–	–	–	–
CG_conf	0.18	–	–	–	–
Lottery	0.17	0.24	0.17	0.15	–
Vaccine	–	–	–	–	–
Balls_1	–	–	–	–	–
Balls_2	–	–	–	0.17	–
Balls_3	0.20	–	–	0.24	–

Table 5.5: Correlation Matrix of Luck Beliefs (PGL, PBL, GBL), luck feelings (LN2, ULN2), and Risky Choice - Correlations of three luck beliefs with two luck feelings measures and nine risky choice measures. See Table 5.2 for risky choice item descriptions. Reported correlations are significant at $p < .05$, and otherwise omitted as indicated by "–".

closeness into account, the conclusions of this results are unclear. Nevertheless, the results of this present analysis do provide some insight into what can be expected later.

Correlations of the two luck feelings measures and the risky choice items are also included in Table 5.5. Note that these correlations are for the entire sample, aggregating both win- and loss-outcome participants. The relationship of luck feelings to risky choice will be further investigated below.

5.5.4 Interaction Effects of Game Outcome and Closeness

In Figure 5.3 and the corresponding discussion, game outcome was shown to be clearly predictive of lucky and unlucky feelings. Will Closeness, taking into account winning and losing, be a better predictor of lucky and unlucky feelings than outcome alone? Which measure of closeness should be used, RD, RD3 or the subjective measure?

To examine this, I conducted three hierarchical regression equations on the two luck feelings measures (LN2 and ULN2). The first hierarchical regression entered Game Outcome and Closeness in the first step, with the interaction of the two in the second step. The second regression replaced RD for Closeness. The third regression replaced RD3 for RD. Recall that each of the closeness measures take the same sign for both winners and losers, so only an interaction effect with game outcome should discern whether the closeness measures predict variance in luck feelings above and beyond game outcome. Results for each of the six regressions are presented in Table 5.6. There were no main effects of RD and RD3, which is uninteresting given that they are exactly equivalent for a each winner and loser for a participant dyad. The main effect of Closeness in the prediction of LN2 is however notable in its statistical significance. This implies that Closeness has a different effect for winners and losers on luck feelings, even though closeness did not differ by game outcome.

The regression parameters are quite different for unlucky feelings. In every case the closeness measures have both main effects and interaction effects with game outcome. The strongest predictor of unlucky feelings among the three closeness measures appears to be the subjective rating (Closeness), with a β value of 0.291, highest among the three interaction terms. Note that the two rolls difference measures take a different sign because they are the inverse of Closeness.

Parallel analyses using the change in luck feelings (Shift_LN2 and Shift_ULN2) as the dependent variables, found a similar pattern to the one presented in Table 5.6. These combined results point to the conclusion that the subjective measure of closeness (Closeness) is the most appropriate to use in testing the counterfactual closeness hypothesis.

The significant interaction term for Game Outcome and Closeness predicting ULN2 warrants inspection of the relationship of Closeness on luck feelings separately for winners and losers. I ran the correlations of Closeness and both LN2 and ULN2 for winners and losers separately. Table 5.7 presents the correlations of Closeness and both LN2 and ULN2, for each game outcome group. For winners, there was no statistically significant relationship of Closeness and LN2. This is a lack of support for the counterfactual closeness hypothesis. But there was an interesting pattern that merits closer inspection. There is additional challenge to this counterfactual closeness hypothesis: close-winners felt more unlucky. I questioned this result, going back to the raw data file, regenerating the variables, and running the tests again. The result was the same. For losers, the Closeness-lucky feelings correlation had the opposite sign of the Closeness-unlucky feelings correlation. It appears that for losers, Closeness was associated with feeling

Step	Variables Entered	LN2			ULN2		
		β	p	adj. R^2	β	p	adj. R^2
1	Game_Won	0.574	0.000	35.9%	-0.558	0.000	33.8%
	Closeness	0.144	0.019		-0.138	0.026	
2	Game_Won	0.575	0.000	35.8%	-0.560	0.000	38.1%
	Closeness	0.190	0.021		-0.334	0.000	
	Game_Won*Closeness	-0.069	0.396		0.291	0.000	
1	Game_Won	0.586	0.000	34.6%	-0.569	0.000	32.7%
	RD	-0.086	0.162		0.092	0.140	
2	Game_Won	0.586	0.000	34.3%	-0.569	0.000	33.8%
	RD	-0.122	0.148		0.206	0.015	
	Game_Won*RD	0.053	0.529		-0.167	0.049	
1	Game_Won	0.588	0.000	34.0%	-0.571	0.000	32.7%
	RD3	-0.045	0.462		0.092	0.139	
2	Game_Won	0.588	0.000	34.4%	-0.571	0.000	34.5%
	RD3	-0.127	0.138		0.232	0.007	
	Game_Won*RD3	0.117	0.169		-0.201	0.019	

Table 5.6: Hierarchical Regressions Predicting Lucky and Unlucky Feelings (LN2 and ULN2 - Results from three sets of regressions, testing different measures of closeness: the subjective rating of game closeness (Closeness), the absolute value of the rolls difference (RD), and the rolls-adjusted absolute value of the rolls difference (RD3). Game Outcome was entered in step 1 as Game_Won (where lost was coded as 0, and won was coded as 1). Closeness, RD or RD3 was also entered at the first step. Entered in step 2 was the interaction term of the closeness measure and game outcome. Interaction terms were created using the z-scores of the closeness measures. Adjusted R^2 is for the model in a given step.

Bivariate Pair	Losers	Winners
Closeness–LN2	0.30	–
Closeness–ULN2	-0.33	0.21

Table 5.7: Correlations of Closeness with LN2 and ULN2 for Winners and Losers - Correlations are significant at the $p < .05$ level.

more lucky and associated with feeling less unlucky. This result is the opposite of that predicted by the counterfactual closeness hypothesis. Instead of feeling more unlucky as a result of 'almost winning', Closeness for losers generates the opposite effect: 'almost-winners' feel more lucky (and less unlucky). Thus, the counterfactual closeness hypothesis is directly challenged by this result.

I used a similar approach to that in Table 5.6 in order to test the interactive effect of game outcome and the closeness measures on risky choice. Across seven risky choice dependent variables, for three different closeness measures (a total of 21 hierarchical regressions) no models approached statistical significance. Although the interaction of game outcome and closeness predicted luck feelings, that same interaction does not predict risky choice.

5.5.5 Summary of Results

This section tested for main effects (on luck feelings and risky choice) of game outcome, closeness, luck beliefs, and the interactive effect of game outcome and closeness. Game outcome had no direct or unique effect on any study variables other than luck feelings. The predominant luck feeling response was the outcome congruent one. In the case of a win-outcome, lucky feelings was increased about twice the magnitude that unlucky feelings decreased. In the case of a loss-outcome, unlucky feelings increased about five times the magnitude that lucky feelings decreased. This is an interesting finding, indicating that outcome congruence to luck feelings is an important consideration.

These analyses also reported that closeness had an equivalent magnitude association with luck feelings, but it was positively associated with lucky feelings and negatively associated with unlucky feelings. Risky choice variables were not associated with closeness. Further understanding of the relationship of closeness to luck feelings was contingent on taking into account the game outcome.

It was found that all luck beliefs had a positive association with both luck feelings. The was a surprising finding, that PGL was shown to correlate with unlucky feelings almost as strongly (and with the same sign) as it did with lucky feelings. The same was true for PBL and lucky feelings. Luck beliefs were shown to have a limited association with risky choice variables. Again, taking game outcome into account is the next step to gaining further insight into these relationships.

Another significant finding from this section is that the subjective closeness measure had better explanatory power of unlucky feelings than did either of the two objective closeness measures. That said, for the lucky feelings measure, the interaction of game outcome and closeness had no additional explanatory power over game outcome alone, an early null finding in the test of the counterfactual closeness hypothesis.

These results reveal a much more complex set of interactions between outcomes, luck feelings, luck beliefs, and counterfactual closeness than previous literature anticipated. For untangling these interactions, a more sophisticated analysis is warranted. Namely, the testing of the general model (from the introductory paragraphs of this chapter) is undertaken in the next section using two separate PLS models. The specification of PLS models for win- and loss-outcome participants can be informed by these previously reported results, namely in the selection of the subjective closeness measure, the appropriateness of taking into account outcome congruent personal luck beliefs on luck feelings, and on the focus on the interaction terms of luck belief and closeness to explain outcome congruent luck feelings. Luck feelings are specified as the antecedents to risky choice, as game outcome, closeness, and the interaction of the two were not associated with risky choice. Luck beliefs did have some association with risky choice, but outcome congruent luck feelings are a logical mediator for these personal beliefs. I now turn to testing of the general model of this chapter, splitting the sample by game outcome.

5.6 PLS Models

5.6.1 Specification of the General Model of Luck Feelings Using PLS

The results of Sections 5.4 and 5.5, together with the general model developed in the introductory paragraphs, provide guidance for specifying a PLS model in the present section. Recall the general model:

$$\textsc{Outcome} \times \textsc{Closeness} \times \textsc{Belief} \;\rightarrow\; \textsc{Feeling} \;\rightarrow\; \textsc{Choice}$$

It describes a relation between three antecedent factors and risky choice, which is mediated by luck feelings. The three factors are Outcome, Closeness, and Belief. As described before, this is a model with three main effects, three two-way interactions, one three-way-interaction, one mediator, and several risky choice dependent variables—with six risky choice variables, there are approximately 12 conceptually permissible paths in this model. Traditional regression techniques are inefficient for such a model, and ANOVA is not recommendable given that two of the antecedent factors are continuous. Model complexity is factorially increased when personal luck belief and luck feeling are expanded to include both PGL and PBL; and both lucky and unlucky feelings. The expanded model would then contain four main effects, five two-way interactions, two three-way interactions, two mediators and several risky choice dependent variables—with six risky choice variables, this expanded model would contain approximately 34 conceptually permissible paths.

Figure 5.5 provides the full model that I will explore for losers and winners separately using PLS. I will conduct a side-by-side comparison of the two measurement and structural models. As can be seen in Figure 5.5, I will include both lucky feelings (LN2) and unlucky feelings (ULN2) as mediating variables for both groups, winners and losers. Although it might be counter-intuitive that non-congruent luck feelings should have an impact on downstream dependent variables (i.e., risky choice), it may be informative to compare the entire system of lucky and unlucky feelings for both groups. I now present the rationale for the arrangement of the elements in the model, and the grouped analyses approach.

5.6.1.1 An Outcome-Grouped Approach

Partial Least Squares Modelling (PLS) is an efficient method of representing a complex system of variables in a theoretically (or at least conceptually) compelling arrangement and analysing their interrelationships simultaneously. A further means of simplifying the analysis is to split the sample by the dichotomous antecedent, outcome. This leads to two separate analyses of the expanded general model above: one for

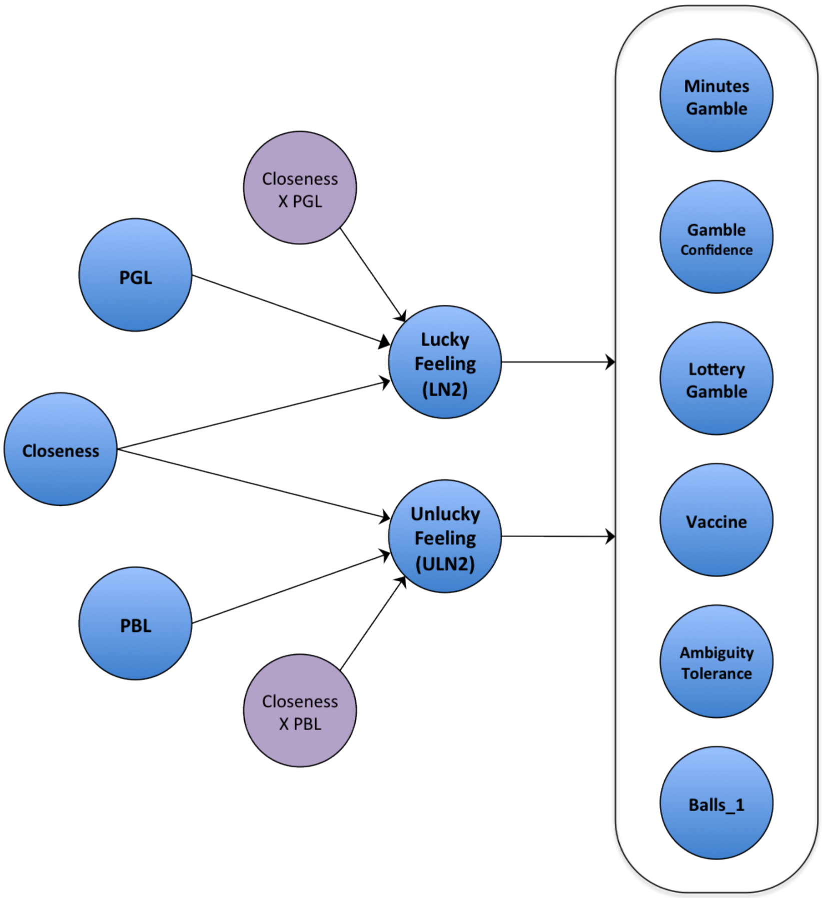

Figure 5.5: Full Model: Lucky and Unlucky Feelings, Risky Choice - A model for exploring risky choice using the system of study variables. Measurement and structural models will be generated separately for winners and losers, and then compared side-by-side. The single arrows from LN2 and ULN2 indicate that paths to all risky choice variables will be tested.

win-outcome participants and one for loss-outcome participants. The models for loss- and win-outcome participants may (and in fact do, as we'll see in a moment) differ to a sufficient degree that the best approach is to explore a general model for only one group at a time. Recall Table 5.3 reported a congruence effect for luck feelings. To wit, there were significant correlations for luck and chance attributions of losers with unlucky feelings (ULN2). For winners though, luck and chance attributions correlated with lucky feelings (LN2). This finding, along with a sensible logic regarding the ways that lucky and unlucky feelings should be differentially affected by win- and loss-outcomes, argue for a split of the dataset by outcome group. One way to understand this rationale is that one chain of paths in the model (i.e., Closeness + PGL + Closeness*PGL $\rightarrow$ LN2 $\rightarrow$ risky choice) is expected to be 'active' for winners, whereas a different chain of paths (i.e., Closeness + PBL + Closeness*PBL $\rightarrow$ ULN2 $\rightarrow$ risky choice) is expected to be active for losers. This prediction is obviously based on an outcome-congruence rationale.

A second finding from Section 5.5 provides a further example of the utility of analysing the general model for each outcome group separately. Recall that a belief in personal bad luck (PBL) was *positively* associated with two risky choice measures. (See Table 5.5 and associated discussion on page 227.) Separating the analyses by outcome groups allows the paths predicting the risky choice variables to be directly compared across the two groups and tested for statistical significance. (The method used for testing differences in path coefficients for groups, PLS-MGA, will be described later.)

The preceding arguments provide both conceptual and empirical grounds to conduct the analyses on each outcome group separately. There is also a practical reason to do so. An attempt to combine the two outcome groups in a single analysis could confound interpretation of any given path in the model. Take for example, the path from closeness to LN2. This is statistically significant when using a combined dataset, but it not possible to determine if it is an active path for winners, losers, or both. (It is in fact *not* statistically significant for winners, but *is* for losers). Using a combined dataset there is only one means to determine whether the path from closeness to LN2 is active for winners, losers or both: an interaction term of outcome and closeness. However, I want to also model the interaction of PGL and closeness. This then requires a three-way interaction to be included in the model. This is theoretically possible, but not very practical or interpretable.

As seen in Figure 5.5, the model contains three main effects, two interactions, two mediators and six risky choice variables—with a total of 18 paths. The same model is tested for both win- and loss-outcome participants. A path in the winners' model, say PGL $\rightarrow$ LN2, can be compared to the same path in the winners model. The comparison is in effect a two-way interaction. When the path being compared contains an interaction in one model, say PGL*Closeness $\rightarrow$ LN2, the comparison across groups is effectively a three-way interaction. Thus, a grouped analysis affords the possibility of comparing the overall models (i.e., are there more constructs or paths in one versus the other?), the 'active' set of paths (i.e., the congruence rationale; winners should feel lucky and losers should feel unlucky), and any specific path of interest (i.e., does closeness differ in sign or magnitude across the winners' and losers' model?).

5.6.1.2 Antecedents of Luck Feelings Measures

For predictors of lucky feelings (LN2) I have included Closeness, PGL, and the interaction of PGL and Closeness. For predictors of unlucky feelings (ULN2) I have included Closeness, PBL, and the interaction of PBL and Closeness. The two interaction terms are a focused test of the counterfactual closeness hypothesis, in effect allowing for the isolation of the effect of closeness to those who are high in belief in luck. I was interested to see if the closeness hypothesis holds for every cell of the 2x2 matrix of lucky-unlucky feelings and winners-losers. Traditionally, the closeness hypothesis would be constrained to include only lucky feelings of winners. That is, the near-loss is thought to generate higher lucky feelings. But, will a near-loss generate lower unlucky feelings for the winner? Will a near-win generate higher unlucky feelings and lower lucky feelings for the loser? To clarify, the predictions from the counterfactual closeness hypothesis are: (1) A close-win results in an individual feeling more lucky, relative to a far-win; and (2) A close-loss results in an individual feeling less lucky, relative to a far-loss. If unlucky feelings are assumed to be inversely related to lucky feelings, the counterfactual closeness hypothesis can be extended to predict that: (3) A close-win results in an individual feeling less unlucky, relative to a far-win; and (4) A close-loss results in an individual feeling more unlucky, relative to a far-loss. These predictions can be represented graphically as a 2x2 matrix of lucky and unlucky feelings crossed by positive and negative outcomes, seen in Figure 5.6. In that figure, each prediction is identified as a number in the corners of the cells.

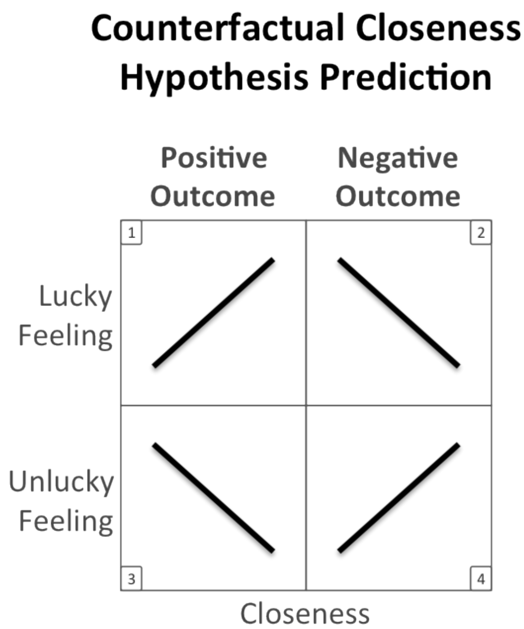

Figure 5.6: Representations of Counterfactual Closeness Hypothesis Predictions - Closeness is along the x-axis for all cells. Luck feelings are on the y-axis. Columns are for a positive outcome (left) and negative outcome (right). Numbers in the corners of cells correspond to descriptions in the text.

Although we have already seen that there are main effects for luck beliefs on some of the risky choice variables, I am primarily interested in the variance explained in risky choice by luck feelings. So, in the specified PLS model, only luck feelings (and not luck beliefs or closeness) are specified to predict risky choice. Note that the relations of the exogenous constructs in the model (i.e., the two personal luck beliefs, closeness, and the interactions of PGL and closeness and PBL and closeness) and the ultimate risky choice dependent variables are reported in the latent variable correlations matrix for the measurement models of each outcome group. Moreover, the mediating effects of the two luck feelings variables can be examined using 'total effects'.

5.6.1.3 Forming Constructs From Risky Choice Measures

One issue not dealt with yet is how to model the risky choice dependent variables. In the risky choice variables portion of the study, participants responded first to a dice-game gamble that was exactly the same as the game in the experimental manipulation, and then secondly to a coin-game gamble. I also included a measure of gamble confidence for both the dice-game gamble and coin-game gamble. In order to test if participants responded differently to the dice-game and coin-game questions, I subjected all four questions [dice-game gamble (DG_mins), coin-game gamble (CG_mins), dice-game gamble confidence (DG_conf), and coin-game gamble confidence (CGconf)] to a factor analysis using principal axis factoring with direct oblimin rotation. Tests for sufficiency of the data for factor analysis were mixed. The KMO test statistic was 0.47, just below the most lenient of thresholds, 0.50 (Kaiser, 1970). Bartlett's test results indicated sufficiency however, with $\chi^2(6) = 240.34$ ($p < .001$). Factor analytic results may therefore not be conclusive, but could be indicative.

Two factors clearly separated the gamble items from the confidence items. Loadings on the first factor were 0.774 and 0.920 for minutes gambled in the dice game (DG_mins) and the coin game (CG_mins) respectively. Loadings on the second factor were 0.767 and 0.821 for gamble confidence in the dice-game (DG_conf) and coin-game (CG_conf) questions respectively. The first factor explained 51% of the variance, and the second factor explained 32%. The correlation of the two gamble questions was 0.713 ($p < .001$). The correlation of the two confidence questions was 0.630 ($p < .001$). A composite of the two gambles questions (average of DG_mins and CG_mins) correlated with a composite of the two confidence questions (average of DG_conf and CG_conf) in a moderate range [$r(177)$=0.229 ($p = .002$)]. Given the strength of the loadings, the amount of variance explained, and the correlations between the items in a given factor, I will group the two minutes questions as indicators for a single *Mins* construct, and I will group the two confidence questions together as a single *Conf* construct.

The remaining five risky choice dependent variables included the vaccine question, the lottery gamble, and the three balls-in-an-urn questions. Only Balls_2 and Balls_3 shared any features. They both were dichotomous response format questions, where one choice provided less certainty about the outcome. In the Balls_2 question, the probability for a winning draw was known for one box, but unknown for a second box. In the Balls_3 question, one box was a certain win, whereas the second box was a probabilistic win that, on expected outcomes, was equivalent to the certain win box. Thus, both of these questions can be combined from a face validity perspective. The combination of these two is verified in the PLS measurement model assessment in Section 5.6. The vaccine question clearly is distinct from all other questions, as it contains no numerical information. The lottery gamble and the Balls_1 share some features, but do not correlate [$r(177) = 0.056$ ($p = .46$)]. I concluded that Balls_2 and Balls_3 should be combined to form an 'ambiguity tolerance' construct (*Ambig*). The remaining variables—lottery gamble and Balls_1—will have single-item indicators[1].

5.6.2 Measurement Model Assessment for Loss-Outcome Participants

Figure 5.7 presents the measurement model for loss-outcome participants. Neither ambiguity tolerance (Ambig) nor Vaccine had significant paths predicting them. The highest t-value was 1.682, for the path from LN2 to Vaccine. I have therefore removed[2] these constructs from the model in Figure 5.7. Note also that the path from the interaction term PBL*Closeness predicting unlucky feelings is only marginally significant ($t(88) = 1.950$).

Measures have already been tested for unidimensionality, namely the risky choice variables immediately above, and the personal luck beliefs in Chapter 3. Measurement model assessment metrics for the loss-outcome participant model are provided in Table 5.8. All items in the model had statistically significant loadings. All composite reliabilities surpassed the recommended level of 0.70. One loading did not exceed the recommended threshold of 0.707. The item, PGL_05 had a loading of 0.59. That loading was however statistically significant ($t(89) = 4.771$), and given there are five indicators for the PGL construct, the low loading for this one item does not pose a

[1] An alternate composition of the model—that specified each risky choice variable as a single indicator for a unique construct—mirrored the results presented below almost exactly.

[2] Best practice in converging on a measurement model stipulates that statistically non-significant paths be removed from the model, and the t-values generated de novo. To do otherwise may result in spurious results, of a Type-II (false-negative) error of eliminating a path that should be retained. Generally speaking, statistically non-significant paths are removed a few at a time, beginning with the lowest t-values. Thus, a path that is marginally significant at first may strengthen when the lower t-value paths are removed. This is equivalent to removing non-significant variables in multiple regression.

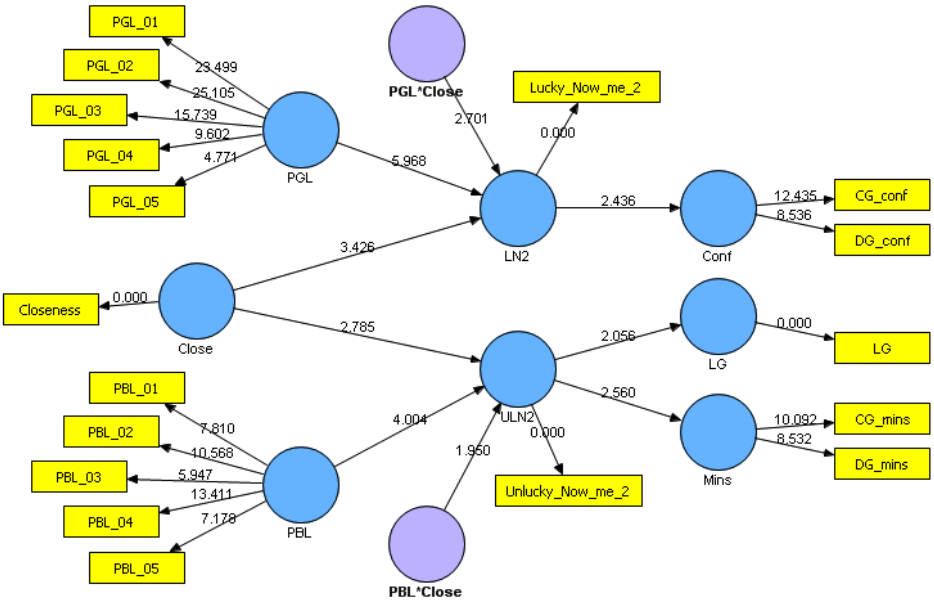

Figure 5.7: PLS Measurement Model of Losers' Risky Choice - Bootstrap t-values (500 resamples) for a proposed PLS model of Closeness, Personal Luck Beliefs (PGL and PBL) and the interactions of luck beliefs and Closeness, predicting lucky (LN2) and unlucky feelings (ULN2), which in turn predict risky choice for loss-outcome participants.

threat to the measurement model. Cross-loadings were without exception below 0.50. All multi-item constructs exceeded the AVE minimum threshold of 0.50. The Fornell-Larcker table did not identify any problematic failures of discriminant validity. In all cases the square root of AVE easily exceeded the latent variable correlations. The measurement model presented for the loss-outcome participants indicates good convergent and discriminant validity.

5.6.3 Measurement Model Assessment for Win-Outcome Participants

Figure 5.8 presents the measurement model for win-outcome participants. Vaccine again had no significant path predicting it. The highest t-value was 1.184, for the path from LN2 to Vaccine. I have therefore removed this construct from the model in Figure 5.8. Note also that the path from the interaction term PBL*Closeness predicting unlucky feelings is only marginally significant as before ($t(88) = 1.953$). Unlucky feelings are non-congruent with the outcome these participants experienced, so that it even marginally significant is unexpected. Note also that the path from closeness (Close) to

	Close	**PGL**	**PBL**	**LN2**	**ULN2**	**Mins**	**LG**	**Conf**
ρ_c	1.00	0.88	0.90	1.00	1.00	0.95	1.00	0.91
Closeness	**1.00**	0.04	-0.17	0.32	-0.32	-0.03	0.11	-0.11
PGL_01	0.08	**0.87**	0.36	0.39	0.18	-0.06	0.00	0.10
PGL_02	0.05	**0.88**	0.31	0.33	0.25	0.09	0.16	0.19
PGL_03	0.07	**0.81**	0.29	0.40	0.22	-0.07	0.08	0.10
PGL_04	-0.01	**0.70**	0.37	0.35	0.06	0.01	0.02	0.15
PGL_05	-0.14	**0.59**	0.44	0.17	0.46	0.18	0.03	0.04
PBL_01	-0.06	0.28	**0.82**	0.25	0.18	0.11	0.12	0.09
PBL_02	-0.10	0.37	**0.90**	0.13	0.31	0.1	0.17	0.04
PBL_03	-0.10	0.22	**0.74**	0.28	0.10	0.14	0.19	0.17
PBL_04	-0.25	0.32	**0.79**	0.12	0.42	0.18	0.17	0.13
PBL_05	-0.06	0.47	**0.75**	0.11	0.27	0.07	0.04	0.14
LN2	0.32	0.44	0.19	**1.00**	-0.20	-0.04	0.00	0.17
ULN2	-0.32	0.26	0.37	-0.20	**1.00**	0.22	0.21	-0.05
DG_mins	0.00	-0.04	0.11	-0.05	0.13	**0.92**	0.23	0.18
CG_mins	-0.05	0.04	0.16	-0.02	0.25	**0.98**	0.22	0.25
LG	0.11	0.07	0.17	0.00	0.21	0.24	**1.00**	0.11
DG_conf	-0.08	0.12	0.08	0.17	-0.13	0.17	0.09	**0.92**
CG_conf	-0.13	0.17	0.17	0.15	0.05	0.26	0.12	**0.91**
AVE	**1.00**	**0.61**	**0.64**	**1.00**	**1.00**	**0.90**	**1.00**	**0.84**
–	**1.00**	–	–	–	–	–	–	–
PGL	0.04	**0.78**	–	–	–	–	–	–
PBL	-0.17	0.43	**0.80**	–	–	–	–	–
LN2	0.32	0.44	0.19	**1.00**	–	–	–	–
ULN2	-0.32	0.26	0.37	-0.20	**1.00**	–	–	–
Mins	-0.03	0.01	0.15	0.00	0.22	**0.95**	–	–
LG	0.11	0.07	0.17	0.01	0.21	0.24	**1.00**	–
Conf	-0.11	0.15	0.13	0.17	-0.05	0.24	0.11	**0.92**

Table 5.8: Measurement Model Assessment for Model of Losers' Risky Choice - Measurement Model Assessment for Losers' Model of Closeness (Close), Personal Luck Beliefs (PGL and PBL) and the interactions of luck beliefs and Closeness (PGL*Close and PBL*Close). These predict lucky feelings (LN2) and unlucky feelings (ULN2), which in turn predict risky choice. See Tables 5.1 and 5.2 for content corresponding to item labels used here.

Provided at top are Composite Reliabilities (Dillon-Goldstein's rho; ρ_c). In the middle section are item loadings (in bold) and cross-loadings, for each item in the model (item labels are to the left). In the lower section is the Fornell-Larcker table with AVE's (horizontally in bold), the square root of the AVE (diagonally in bold) and latent variable to latent variable correlations.

lucky feelings (LN2) is not statistically significant reflecting the lack of finding reported in Table 5.7. The path must be retained in the model to create the interaction term.

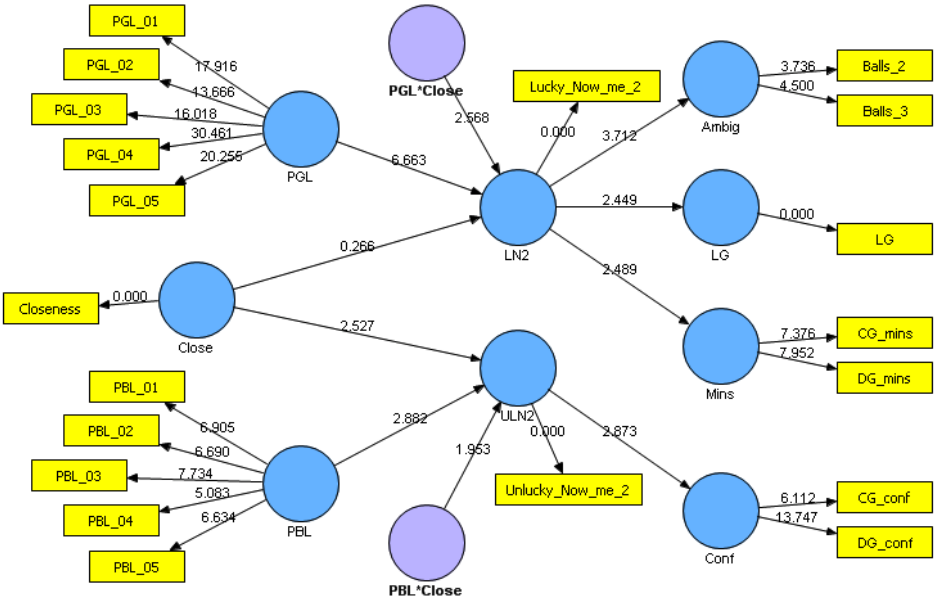

Figure 5.8: PLS Measurement Model of Winners' Risky Choice - Bootstrap t-values (500 resamples) for a proposed PLS model of Closeness, Personal Luck Beliefs (PGL and PBL) and the interactions of luck beliefs and Closeness, predicting lucky (LN2) and unlucky feelings (ULN2) for win-outcome participants.

Measurement model assessment metrics for the win-outcome participant model are provided in Table 5.9. All items in the model had statistically significant loadings except the aforementioned path, Close $\rightarrow$ LN2, which was retained for the interaction term. Again, all composite reliabilities surpassed the recommended level of 0.70. All loadings exceeded the recommended threshold of 0.707. The items PBL_01 and PBL_04 exceeded the recommended cross-loadings threshold of 0.50 for the PGL construct, with 0.51 and 0.58 respectively. Similarly, three items from the PGL construct marginally exceeded the threshold for the PBL construct. Given the high correlation of PGL and PBL (0.56; see the Fornell-Larcker section of Table 5.9) this is not surprising and not cause for concern. All multi-item constructs exceeded the AVE minimum threshold of 0.50. The construct for ambiguity tolerance was the lowest of all, at 0.58, which is still strong enough to warrant combining Balls_2 and Balls_3 to form the Ambig construct. The Fornell-Larcker table did not identify any problematic failures of discriminant validity.

In all cases the square root of AVE easily exceeds the latent variable correlations. As before, the measurement model presented for the win-outcome participants indicates good convergent and discriminant validity.

5.6.4 Structural Models Overview

The structural model for loss-outcome participants, with β values for each path and R^2 values for each endogenous latent variable, is presented in Figure 5.9. The structural model for win-outcome participants is presented in Figure 5.10. I discuss the loss-outcome model first, then the win-outcome model, comparing the two directly.

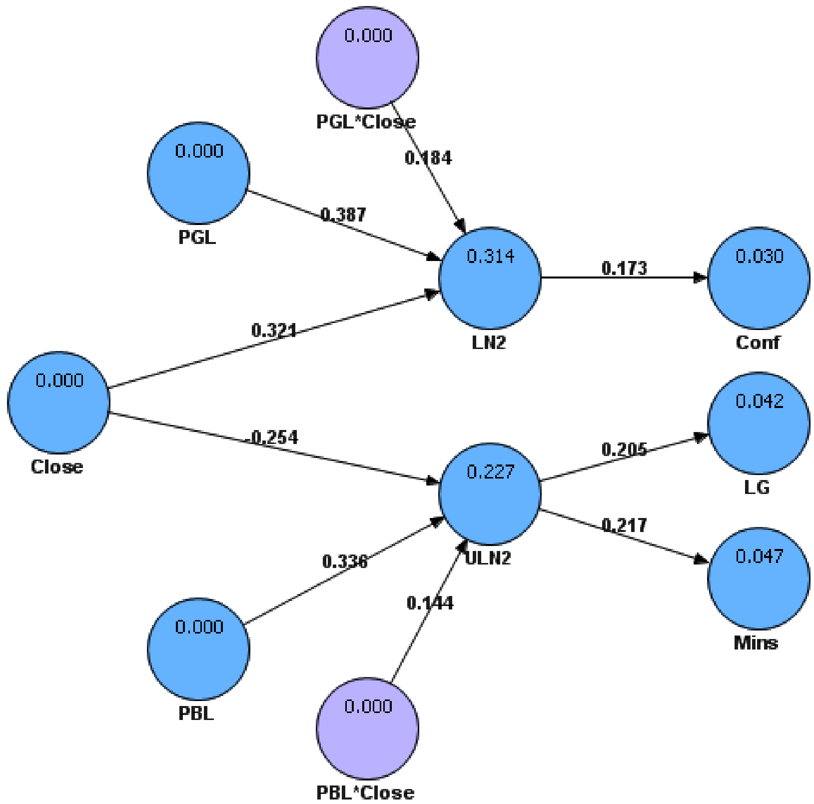

Figure 5.9: PLS Structural Model of Losers' Risky Choice - Parameter estimates (path βs on the lines; R^2 values inside each construct) for the model of Losers' Risky Choice. Note that the path from Close to ULN2 is -0.254; the sign is partly obscured in the figure.

	Close	PGL	PBL	LN2	ULN2	Mins	LG	Ambig	Conf
ρ_c	1.00	0.92	0.93	1.00	1.00	0.89	1.00	0.73	0.88
Closeness	**1.00**	0.15	0.02	0.09	0.20	0.08	-0.08	-0.07	0.08
PGL_01	0.11	**0.85**	0.40	0.39	0.05	0.25	0.20	0.15	0.26
PGL_02	0.13	**0.84**	0.53	0.37	0.11	0.29	0.23	0.14	0.26
PGL_03	0.10	**0.81**	0.32	0.44	0.02	0.19	0.15	-0.01	0.23
PGL_04	0.13	**0.84**	0.54	0.49	0.20	0.16	0.17	0.22	0.33
PGL_05	0.12	**0.80**	0.52	0.49	0.05	0.16	0.19	0.12	0.05
PBL_01	0.08	0.51	**0.85**	0.35	0.13	0.15	0.23	0.14	0.01
PBL_02	0.10	0.49	**0.87**	0.39	0.08	0.14	0.26	0.01	0.07
PBL_03	-0.05	0.42	**0.93**	0.26	0.26	-0.03	0.16	0.02	0.09
PBL_04	0.06	0.58	**0.77**	0.44	0.12	0.11	0.31	0.27	0.12
PBL_05	0.01	0.48	**0.81**	0.29	0.15	0.20	0.16	0.00	0.23
LN2	0.09	0.53	0.38	**1.00**	-0.07	0.19	0.26	0.35	0.15
ULN2	0.20	0.11	0.20	-0.07	**1.00**	-0.03	-0.14	-0.09	0.25
DG_mins	0.11	0.22	0.07	0.18	-0.02	**0.90**	0.28	0.08	0.24
CG_mins	0.03	0.22	0.12	0.17	-0.03	**0.89**	0.34	0.10	0.25
LG	-0.08	0.22	0.24	0.26	-0.14	0.35	**1.00**	0.14	0.16
Balls_2	0.04	0.08	0.02	0.25	-0.18	0.17	0.10	**0.73**	-0.02
Balls_3	-0.14	0.15	0.12	0.28	0.03	-0.01	0.11	**0.79**	0.11
DG_conf	0.08	0.24	0.14	0.11	0.26	0.21	0.14	0.05	**0.93**
CG_conf	0.07	0.25	0.07	0.17	0.17	0.30	0.15	0.06	**0.83**
AVE	**1.00**	**0.69**	**0.72**	**1.00**	**1.00**	**0.80**	**1.00**	**0.58**	**0.78**
–	**1.00**	–	–	–	–	–	–	–	–
PGL	0.15	**0.83**	–	–	–	–	–	–	–
PBL	0.02	0.56	**0.85**	–	–	–	–	–	–
LN2	0.09	0.53	0.38	**1.00**	–	–	–	–	–
ULN2	0.20	0.11	0.20	-0.07	**1.00**	–	–	–	–
Mins	0.08	0.25	0.10	0.00	-0.03	**0.90**	–	–	–
LG	-0.08	0.22	0.24	0.26	-0.14	0.35	**1.00**	–	–
Ambig	-0.07	0.15	0.09	0.35	-0.09	0.10	0.14	**0.76**	–
Conf	0.08	0.27	0.12	0.15	0.25	0.27	0.16	0.07	**0.88**

Table 5.9: Measurement Model Assessment for Model of Winners' Risky Choice - Measurement Model Assessment for Winners' Model of Closeness (Close), Personal Luck Beliefs (PGL and PBL) and the interactions of luck beliefs and Closeness (PGL*Close and PBL*Close). These predict lucky feelings (LN2) and unlucky feelings (ULN2), which in turn predict risky choice. See Tables 5.1 and 5.2 for content corresponding to item labels used here.

Provided at top are Composite Reliabilities (Dillon-Goldstein's rho; ρ_c). In the middle section are item loadings (in bold) and cross-loadings, for each item in the model (item labels are to the left). In the lower section is the Fornell-Larcker table with AVE's (horizontally in bold), the square root of the AVE (diagonally in bold) and latent variable to latent variable correlations.

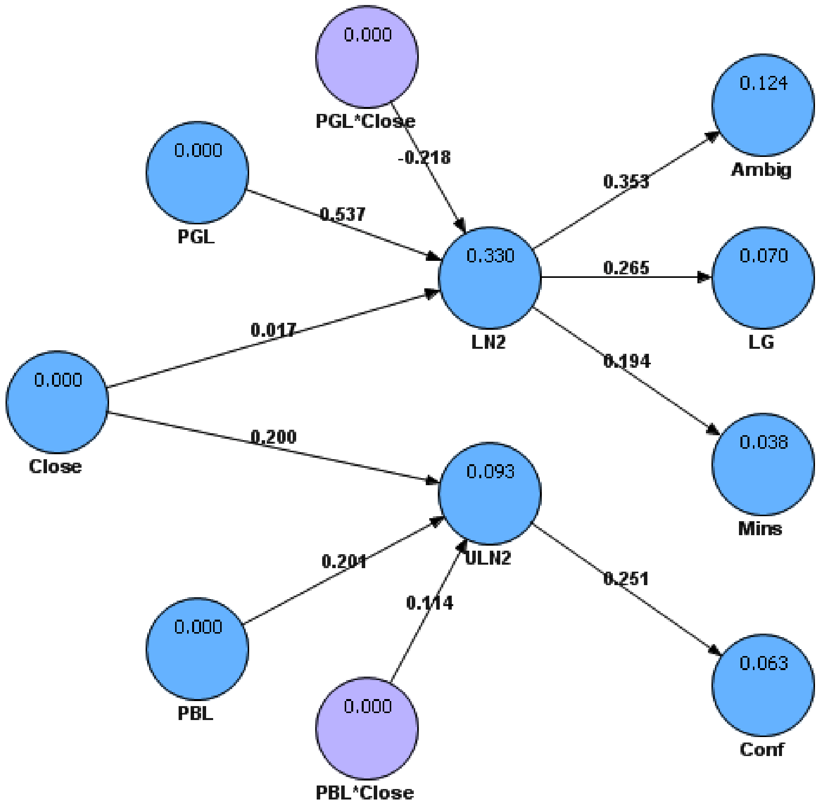

Figure 5.10: PLS Structural Model of Winners' Risky Choice - Parameter estimates for the model of Losers' Risky Choice. Note that the path from Close to LN2 is not statistically significant but is retained to form the interaction term of PGL*Close.

5.6.5 Structural Model Assessment for Loss-Outcome Participants

I first call attention to the path coefficients of the loss-outcome model presented in Figure 5.9. The paths from Close to LN2 and ULN2 reflect the pattern found for loss-outcome participants in Table 5.7. Namely, that for losers, closeness is positively related to lucky feelings and negatively related to unlucky feelings. The paths from PGL to LN2 and PBL to ULN2 are both positive, as would be expected: luck beliefs should predict the congruent luck feeling. A test of the paths for the non-congruent luck feeling indicated that the path from PGL to ULN2 was statistically significant (t (88)=2.121), whereas the path from PBL to LN2 was not (t (88)=1.056). The PGL-ULN2 construct correlation is 0.26, reported in the Fornell-Larcker portion of Table 5.8.

The path from the interaction term for PGL*Close to LN2 was statistically significant, but the positive sign is difficult to interpret without examining the means for LN2 across the 2x2 of (median splits of) closeness and PGL. The LN2 group mean for participants who were both high-PGL and high-closeness was 2.10, the highest among the four cells. The four means are reported in the upper section of Table 5.10. Although the path for the interaction term of PBL*Close to ULN2 was only marginally significant, it is nevertheless instructive to examine the pattern for the means of ULN2 across the 2x2 of (median splits of) closeness and PBL. The highest mean of ULN2 (i.e., the most strong unlucky feeling) was for the group comprised by participants who were both high-PBL and high-closeness, 3.17. The four means are also reported in Table 5.10.

The pattern of interactions supports a view that personal luck beliefs positively moderate the relationships between closeness and luck feelings seen in the model in Figure 5.9. In the context of closeness and LN2, the positive path coefficient is strengthened by the presence PGL. When a participant had a high belief in personal good luck, a close game led to a higher lucky feeling. On the other hand, in the context of closeness and ULN2, the negative path coefficient is strengthened by the presence of PBL. When a participant had a high belief in personal bad luck, a ‘far’ game led to a higher unlucky feeling.

Looking now to the coefficients for the luck feelings → risky choice paths, there were three paths to risky choice that were statistically significant. For loss-outcome participants, the (outcome congruent) *un*lucky feeling is associated with increases in two types of risky choice, whereas the outcome non-congruent luck feeling is associated

Loss-Outcome Participants

	Group Means of LN2			Group Means of ULN2	
	Low PGL	High PGL		Low PBL	High PBL
High Closeness	1.40	2.10	High Closeness	1.96	2.58
Low Closeness	1.16	1.46	Low Closeness	2.78	3.17

Win-Outcome Participants

	Group Means of LN2			Group Means of ULN2	
	Low PGL	High PGL		Low PBL	High PBL
High Closeness	2.64	3.27	High Closeness	1.30	1.52
Low Closeness	2.24	3.67	Low Closeness	1.10	1.16

Table 5.10: Luck Feelings Means, by Game Outcome, Closeness, and Luck Belief - Means for luck feelings are reported. A total of 16 means are reported for the 2 x 2 x 2 x 2 factorial structure of Luck feeling (LN2, ULN2) Game Outcome (Win, Loss) x outcome congruent luck belief (high, low) x Closeness (high, low). High-Low groups were created using a median-split for PGL, PBL, and Closeness.

with an increase in confidence. Both of these are somewhat surprising findings. I did not expect the outcome non-congruent luck feeling to be associated with any of the risky choice measures, including confidence. I also did not expect unlucky feelings to be *positively* associated with risky choice, but rather thought that feeling unlucky should lead to a reduction in risky choice. The R^2 values in these risky choice and confidence variables are small though, ranging between 0.030 and 0.047, even though the path coefficients are in a mid-range. As an indication of the extent of the effect of ULN2 on Conf, using the mean of the two constituent confidence measures as a confidence scale, the confidence scale means for median-split (for losers only) of LN2 were 50.44 (high LN2) and 42.80 (low LN2).

The differences in the risky choice variables using a median-split of ULN2 were of a similar magnitude. Using the mean of the dice-game and coin-game gambles to create a Minutes scale, the Minutes scale means for median-split (for losers only) of ULN2 were 20.77 (low ULN2) and 29.36 (high ULN2). For the lottery gamble, the means for the same groups were 4.00 and 4.63. In both cases, a higher *un*lucky feeling was associated with an increase in risky choice.

Notice the R^2 values of LN2 and ULN2 for the losers' model. These were quite high at 0.314 and 0.227 respectively. What happens to the variance explained when predictors are removed from the model though? That is, which of the predictors makes the greatest (or least) contribution? A Cohen's f^2 allows for this comparison[1]. Table 5.11 presents the R^2 values for three alternative model compositions. The upper block is the model for loss-outcome participants. The lower block is the model for win-outcome participants, which will be discussed later. The Cohen's f^2 values for each of the correspondingly removed predictors is also provided (on the right-hand side) of that same table. For the losers' model, the interaction terms make only a small contribution to the R^2 values, as can be seen by the decrease in the R^2 value to 0.28 and 0.21 for LN2 and ULN2 respectively. The Cohen's f^2 values are therefore low at 0.05 and 0.03 for LN2 and ULN2 respectively. The greatest contribution to the variance explained in the luck feelings measures is from luck beliefs and their interactions with Close, which together had a Cohen's f^2 of 0.31 for LN2, and only about half that for ULN2. Closeness was also quite high in its contribution to variance explained of luck feelings, with a Cohen's f^2 of 0.18 and 0.11 for LN2 and ULN2 respectively. The general impression that emerges is that luck beliefs play the greatest role in predicting lucky feelings for both winners and losers.

5.6.5.1 Total Effects

Looking to total effects in the losers' model, there are nine total effects paths with a mediating construct. Only one of these total effects reached statistical significance, that of PGL $\rightarrow$ LN2 $\rightarrow$ Conf. That path had a t-value of 2.262 and a β value of 0.067, quite small indeed. An informal assessment of mediation demonstrated that PGL had a direct relationship with Conf when all other constructs were excluded from the model (t-value of 2.160 and a β value of 0.173), but this direct path was rendered non-significant when LN2 was added back to the model (t=0.945).

5.6.6 Structural Model Assessment for Win-Outcome Participants

I now call attention to the path coefficients of the win-outcome model presented in Figure 5.10. The paths from Close to LN2 and ULN2 again reflect the findings presented

[1] Cohen's f^2 was previously described and used on page 171.

Loss-Outcome Model

Predictors Included	R^2 LN2	R^2 ULN2	Cohen's f^2 LN2	Cohen's f^2 ULN2	Predictors Excluded
Full Model	0.31	0.23	–	–	–
Closeness; Luck Beliefs	0.28	0.21	0.05	0.03	Interaction terms
Closeness	0.10	0.10	0.31	0.16	Luck Beliefs; Interactions
Luck Beliefs	0.19	0.14	0.18	0.11	Closeness; Interactions

Win-Outcome Model

Predictors Included	R^2 LN2	R^2 ULN2	Cohen's f^2 LN2	Cohen's f^2 ULN2	Predictors Excluded
Full Model	0.33	0.09	–	–	–
Closeness; Luck Beliefs	0.28	0.08	0.07	0.01	Interaction terms
Closeness	0.01	0.04	0.48	0.06	Luck Beliefs; Interactions
Luck Beliefs	0.28	0.04	0.07	0.06	Closeness; Interactions

Table 5.11: Variance Explained (R^2) in Lucky Feelings (LN2) and Unlucky Feelings (ULN2) for Alternate Model Compositions - Cohen's f^2 is reported for omitted constructs corresponding to each alternate model. The upper block is the model for loss-outcome participants. The lower block is the model for win-outcome participants.

in Table 5.7. For winners, closeness predicts only ULN2, and does so positively: as perceptions of game closeness increase there is a corresponding increase in *un*lucky feelings. The path from Close to LN2 was not statistically significant, but must be retained in the model in order to create the interaction term PGL*Close. The two personal luck beliefs again predict congruent luck feelings positively, just as they did for losers, and in line with expectations.

The path from the interaction term of PGL*Close to LN2 is negative. The path for the interaction term of PBL*Close to ULN2 was marginally significant, and is reported as positive in the model in Figure 5.10. In order to interpret these paths, I calculated the means for LN2 and ULN2 as before, using a median-split of Close and the feeling-congruent luck belief.

The group mean for LN2 for participants who were both high-PGL, high-closeness was 3.67, the highest among the four cells. The four LN2 means are reported in the lower section of Table 5.10. The group comprised by participants who were both high-PBL and high-closeness had the highest mean ULN2 (i.e., the most strong unlucky feeling), 1.52. The four ULN2 means are also reported in Table 5.10.

As with the losers' model, the pattern of interactions in the winners' model supports a view that personal luck beliefs strengthen the relationships between closeness and luck feelings seen in the model in Figure 5.10. In the context of closeness and LN2, there was no statistically significant path coefficient, but when PGL is taken into account, closeness is inversely related to LN2. When a winning participant had a high belief in personal good luck, a 'far' game led to a higher lucky feeling. On the other hand, in the context of closeness and ULN2, the positive path coefficient is strengthened by the presence of PBL. On average, when a participant had a high belief in personal bad luck, a close game led to a higher unlucky feeling.

5.6.7 Comparisons of Structural Models

I return now to Table 5.11, to examine the R^2 values for alternate compositions of the winners' model. Though not surprising, the most striking observation is that the R^2 for ULN2 in the winners' model is less than half of that in the losers' model. It appears that the *un*lucky feelings of winners are not very well explained by the full model. The variance explained is mostly split between closeness and PBL (the outcome non-congruent personal luck belief). As regards the outcome-congruent luck feeling measure (LN2), PGL and the interaction of PGL and closeness has a very large Cohen's f^2 of 0.48 indicating that these predictors are very strong relative to closeness. The closeness measure alone predicts virtually no variance in LN2.

Comparing the average variance explained for LN2 and ULN2 across alternate models for losers and winners yields further insight. The full model for losers explains an average of 27% in luck feelings combined, whereas the full model for winners' explains an average of 21%. So the full model for losers provides about three-fourths of the explanatory power compared to the full model for winners. However, when only closeness is used as predictor, the average variance explained in LN2 and ULN2 in the losers' model is 10%. The winners' model provides only about one-fifth of the explanatory power in luck feeling using only closeness as a predictor, 2%. This is a very different case when only luck belief is used as a predictor, the average variance explained for LN2 and ULN2 is almost equivalent for winners' and losers' models, 17% and 16% respectively.

Turning now to the impact of luck feelings on risky choice, the pattern for the winners' model is very different from that of the losers' model. Namely, lucky feelings for winners predict the risk measures, whereas unlucky feelings predict confidence. For losers, this general pattern is inverted. It is unlucky feelings that predict the risk measures, whereas lucky feelings predict confidence. Using the congruence perspective, this inverted pattern for winners and losers models is interpreted as luck feelings having the same effects on risky choice and confidence: It is the outcome-congruent luck feeling that predicts risky choice, whereas the outcome non-congruent luck feeling predicts confidence. The congruent perspective provides an elegantly simple summary of the combined results.

There was one notable exception to this pattern vis-a-vis the risky choice measures. For both winners and losers, minutes gambled (Mins) and lottery gamble (LG) was predicted by the outcome-congruent luck feeling. But for winners, lucky feelings (the outcome-congruent luck feeling) predicts a third risky choice construct: ambiguity tolerance (Ambig). In fact, the strongest β and R^2 values among all risky choice dependent variables (for both the loss- and win-outcome models) are for Ambig in the winners' model. The losers' model did not predict Ambig.

5.6.8 Comparison of Path Coefficients in Loss- and Win-Outcome Models

For a more in-depth comparison between winners and losers path coefficients, the β values for each of the paths in the losers' and winners' model are compared in Table 5.12. Column A in that table lists the predictor construct, and Column B lists the predicted construct. Columns C and D provide path coefficients for the losers and winners respectively. Note that only two paths differ in sign across the winners' and losers' model. Namely, the path from Close to ULN2 and the path from the interaction term of PGL*Close to LN2. Column E of Table 5.12 lists the difference between each path for winners' and losers' models. That difference is calculated as the β value for a given path in the losers' model minus the β value for that same path in the winners' model. Column F is described in a moment.

For the predictors of luck feelings, the path with the greatest difference was that of Close $\rightarrow$ ULN2, at -0.454 (see Row 2). Nearing that magnitude was difference in the paths from the PGL*Close interaction term to LN2 (Row 5). There was also a large difference for the path, Close $\rightarrow$ LN2, 0.304 (Row 1). This difference approaches the magnitude the differences of the paths in Rows 2 and 5, for which the signs differed across the losers' and winners' model. There is almost no difference in the path from the interaction term of PBL*Close to ULN2 (Row 6).

There were three risky choice constructs shared across the losers' and winners' models. As described previously, the outcome congruent luck feeling predicted risky choice, whereas the outcome non-congruent feeling predicted confidence. A interesting set of questions arises from this: Do the outcome congruent luck feelings differ in their prediction of risky choice for winners and losers?; and, Do the outcome non-congruent luck feelings differ in their prediction of confidence for winners and losers? To address this question, I compare the outcome congruent luck feeling path coefficients for risky choice (LG and Mins), as well a the non-congruent luck feeling path coefficient to the confidence construct (Conf). The differences reported are very close to zero, indicating that for winners and losers there is almost no difference between the prediction-ability of an outcome congruent luck feeling for risky choice. Similarly, there is almost no difference between the prediction-ability of an outcome non-congruent luck feeling for confidence. This is indeed a surprising finding. Again, why would risky choice *increase* for an unlucky feeling, even though it is congruent with the outcome? I return to this question in the discussion.

5.6.8.1 Total Effects

What total effects are there in the winners' model? There were twelve total effects paths that contained a mediating construct. The statistically significant total effects in the model were limited to three paths involving PGL, LN2 and risky choice (not including confidence). The β value for path from PGL $\rightarrow$ LG was 0.142 (t=2.21), and for the path from PGL $\rightarrow$ Ambig was 0.189 (t=3.47). The path from PGL $\rightarrow$ Mins was marginally significant at 0.104 (t=1.945). Looking at mediation of LN2 in the relationship of PGL to these three risky choice constructs, I included a direct path from PGL to all three and removed all other constructs and paths. Not a single path from PGL to any of the three risky choice variables was statistically significant, so LN2 could not mediate because there was no direct effect for participants experiencing a win-outcome[1]. Recall that the losers' model found a significant mediation for PGL $\rightarrow$ LN2 $\rightarrow$ Conf. Perhaps for some

[1] In accordance with the results presented in Table 5.5, when these same paths were tested using the whole sample, including both winners and losers, all three paths were significant ($t > .2.45$), and the β values were: 0.210 for the path to Ambig; 0.181 for the path to LG; and 0.162 for the path to Mins.

	(A)	(B)	(C)	(D)	(E)	(F)
	Path		β values			
	Predictor	Predicted	Losers' Model	Winners' Model	Difference	p-value
1)	Close	LN2	0.321	0.017	0.304	$< .001$
2)	Close	ULN2	-0.254	0.200	-0.454	$.008$
3)	PGL	LN2	0.387	0.537	-0.150	$.065$
4)	PBL	ULN2	0.336	0.201	0.135	$.116$
5)	PGL*Close	LN2	0.184	-0.218	0.402	$< .001$
6)	PBL*Close	ULN2	0.144	0.114	0.030	–
7)	LN2	Conf	0.173	*ns*	-0.078	–
	ULN2		*ns*	0.251		–
8)	ULN2	LG	0.205	*ns*	-0.060	–
	LN2		*ns*	0.265		–
9)	ULN2	Mins	0.217	*ns*	-0.023	–
	LN2		*ns*	0.194		–
10)	LN2	Ambig	*ns*	0.353	–	–

Table 5.12: Path Coefficients of Losers' and Winners' Model Compared - The predictor construct is listed in Column A. Column B lists the predicted construct. Columns C and D list the β values for a given path in the losers' model and winners' model respectively. Column E lists the difference between (C) and (D). Column F lists the p-value of the PLS-MGA test for differences in path coefficients. Note that Conf, LG, and Mins are common across the two models, although the predictor construct differs. The difference is nevertheless calculated even though the path originates from different predictor constructs: see text for explanation of the rationale.

loss-outcome participants, the belief in personal good luck buoyed lucky feelings and confidence in the face of a lose.

5.6.9 PLS-MGA Tests for Group Differences of Select Path Coefficients

I now conduct a series of statistical significance tests on the differences in the path coefficients reported in Column E of Table 5.12. The p-values of the tests can be found in Column F of that same table. A technique to test for group differences on PLS-generated model parameters (i.e., path coefficients) was originally proposed in Henseler (2007) and further explicated in Henseler, Ringle & Sinkovics (2009). I will hereafter refer to this method as PLS-MGA in accordance with Henseler et al. (2009). The PLS-MGA is fully described in Henseler et al. (2009), and an overview is provided in the Appendix. It should be noted that Equation 11 in Henseler et al. (2009, p. 309), which is the final statement of the PLS-MGA, is misprinted or mistaken (Henseler, 2011). My understanding from Henseler (2011) is that it should read as follows (with notation being that used and defined in Henseler et al. (2009)):

$$P(b^{(1)} > b^{(2)} | \beta^{(1)} \leq \beta^{(2)}) = 1 - \frac{\sum\limits_{\forall j,i} b^{(2)} - \beta^{(1)} - (b^{(2)} - \beta^{(2)}) - b_j^{(1)} + b_i^{(2)}}{J^{(2)}}$$

The PLS-MGA is a non-parametric method sharing some features of the Mann-Whitney-Wilcoxon matched pairs test. An advantage of the PLS-MGA comparison approach is that the model parameters for winners and losers can be compared directly regardless of the extent to which model composition is similar. Differences in path coefficients across the two models are effectively two-way interaction effects. However, the test of path differences for interaction terms is a three-way interaction. Three-way interactions are laborious to test and comprehend using traditional techniques, but are much more easily interpretable when using a PLS-MGA approach.

I conducted five PLS-MGA tests for group differences between losers' and winners' models. Recall that Table 5.12 lists in Column E the differences in question and in Column F list the p-value of a differences test. The first path difference I tested was that of Close $\rightarrow$ LN2, from Table 5.12. Even though the path coefficient for winners was not statistically significant, this test used the actual path coefficient estimates for winners rather than zero. Not surprisingly, the result was statistically significant ($p < .001$). This test is not problematic even though one path is not statistically significant (Henseler, 2012). The second path I tested was Close $\rightarrow$ ULN2. It also was statistically significant ($p = .008$). There is clearly a difference by game outcome in the effect of closeness on unlucky feelings ($p = .008$).

Two additional paths were tested for differences by game outcome: PGL $\rightarrow$ LN2 ($p = .065$); and PBL $\rightarrow$ ULN2 ($p = .116$). These are the paths presented in Rows 3 and 4 in Table 5.12, and can be referred to as belief-congruent luck feelings. Neither of these had a difference that was statistically significant, though the path from PGL to LN2 was close. Taken conservatively, this result fails to show a difference across game outcome for the main effect of personal luck beliefs on belief-congruent luck feelings. Of course, this is a null result, but it is indicative of the sort of pattern one would expect to find. Being a stable individual difference, PGL and PBL should relate to their belief-congruent luck feelings in a fairly stable manner, when outcome or closeness are not taken into account as moderators. There was some suggestion from the results above that PGL might buoy lucky feelings among loss-outcome participants, but if it did, the effect was not stronger than the same effect for win-outcome participants.

The last path I tested for a difference by game outcome was Close*PGL $\rightarrow$ LN2. It was statistically significant ($p < .001$). I did not test the remaining paths because the differences were so small. Nevertheless, path differences for rows 7, 8 and 9 deserve some further attention and interpretation. These are again null effects, so caution must be taken in forming a solid conclusion. However, the comparison of the path coefficients for winners and losers is suggestive that there are no differences in the effects on risky choice across for outcome-congruent luck feelings. To clarify, take path 8 for example, I have compared the path coefficient of loss-outcome participants from ULN2 to LG to the path coefficient for win-outcome participants from LN2 to LG. The difference is negligible, at -0.060. That the path coefficients have the same sign for both game outcomes is surprising, that there is no meaningful difference between the coefficients is even more so. This is the same pattern for Path 9, and for Path 7, which is the effect of outcome non-congruent luck feeling on confidence compared by game outcome.

There is little doubt that the path in Row 10 differs for winners and losers. The path was removed from the model for losers, so I had no bootstrap estimates available for comparison. However, the difference is in the range of those in Rows 1, 2 and 5 and therefore can be taken as similarly statistically significant.

Comparisons of path coefficients fall into primarily three categories. The first is the effect of closeness on luck feelings. For winners and losers, there were significant differences in the prediction of closeness and lucky feelings, though winners' lucky feelings were not actually predicted by closeness. There were also significant differences in the prediction of closeness and unlucky feelings, with closeness being negatively related to unlucky feelings for losers (i.e., close-losers felt less unlucky) and closeness being positively related to unlucky feelings for winners (i.e., close-winners felt more unlucky. The second category and third category of comparisons are based on the absence of a finding, but nevertheless are instructive. The two personal luck beliefs relationship with belief-congruent luck feelings make up the second category. As one would expect, a belief in personal good luck was similarly predictive of lucky feelings for winners and losers (when no moderators were taken into account such as outcome or closeness). Also in line with expectations, a belief in personal bad luck was similarly predictive of unlucky feelings for winners and losers (again, when no moderators were taken into account such as outcome or closeness). The third category of comparisons was for outcome congruent luck feelings and risky choice, and outcome non-congruent luck feelings and confidence. Across the winners' and losers' models, there was no difference found in the relationship between outcome-congruent luck feeling and risky choice. There was also no difference found in the relationship between outcome non-congruent luck feeling and confidence.

5.6.10 Summary of PLS Results

To begin the PLS analyses, I aggregated the risky choice dependent variables to form six constructs, three of which had multiple indicators. The Mins construct was made up of the two minutes gamble items, DG_mins and CG_Mins. The Conf construct was made up of two gamble confidence items, DG_conf and CG_conf. The Ambig construct was made up of Balls_2 and Balls_3. Vaccine, Balls_1 and LG all had single indictors for each. No paths from luck feelings to either Vaccine or Balls_1 were statistically significant.

I specified and tested the general model, splitting the sample into two groups by game outcome. Thus, there were two measurement model assessments and two structural model assessments. The measurement models for both loss- and win-outcome participants demonstrated good convergent and divergent validity. Composite reliabilities and AVE's exceeded minimum threshold criteria. Loadings were above 0.707 with the exception of a single item for PBL in the win-outcome model. This was acceptable given the construct was reflective with five items, and that it had been previously validated in Chapter 3 using the full sample. Cross-loadings were below 0.50 for all items, and the Fornell-Larcker table revealed no problems with divergent validity for the construct-to-construct relations. The path from Close to LN2 for winners was not statistically significant, but retained in the model for sake of the interaction term of PGL*Close.

Structural model assessment began with the loss-outcome model and proceeded to the win-outcome model with comparisons between the two. The key findings from these model assessments centre on (1) the differential relationship of closeness to luck feelings depending on outcome, (2) the moderating role of personal luck beliefs on the relationship between closeness and luck feelings, and (3 the identification of outcome-congruent luck feelings as the active predictor of risky choice, regardless of outcome.

To summarise the first key PLS finding, recall results presented in Table 5.10. That table reported lucky and unlucky feelings means for median-split groups of closeness, PGL and PBL, by game outcome, for a total of 16 means. For lucky feelings of win-outcome participants, the group with the highest mean was that comprised of low closeness, high PGL participants. For unlucky feelings of loss-outcome participants, the group with the highest mean was also that comprised of low closeness, high PBL participants. Outcome congruent luck feelings have a similar response to closeness and outcome congruent luck belief for both winners and losers, which is that *closeness is inversely related to outcome congruent luck feelings for high luck belief participants*.

The story was much the same for the outcome non-congruent luck feelings. That is, outcome non-congruent luck feelings have a similar response to closeness and outcome non-congruent luck belief for both winners and losers. For lucky feelings of loss-outcome participants, the group with the highest mean was that comprised of high closeness, high PGL participants. For unlucky feelings of win-outcome participants, the group with the highest mean was also that comprised of high closeness, high PBL participants. Thus, *closeness is directly related to outcome non-congruent luck feelings for high luck belief participants*.

To summarise the second key PLS finding, Figure 5.11 provides a stylised illustration of the effects of closeness on lucky and unlucky feelings taking into account game outcome in the left-hand matrix. (The matrix to the right is introduced in the next paragraph.) There are eight total plots in the figure. The x-axis is the same for all plots: closeness increases moving right. The y-axis for the top row of plots is lucky feeling, increasing upward. For the bottom row, it is unlucky feeling, also increasing upward. Note that each cell has a unique identifier. To clarify how to read the figure, take Cell c in the bottom left for example: As closeness increases, winners feel more unlucky. Cell d then would demonstrate that as closeness increases, losers feel less unlucky. The slopes are stylised and not meant to be interpreted as representative of the actual slope, but rather the direction of the relationship. The matrix of to the left is for all participants.

The matrix to the right is for high congruent personal luck belief participants. The congruent personal luck belief for luck feelings is PGL, whereas the congruent personal luck belief of unlucky feelings is PBL. So as an example, Cell D in the bottom right illustrates that for high-PBL losers, as closeness increases they feel less unlucky. As a further example, for Cell A illustrates that for high-PGL winners, as closeness increases they feel less lucky. As can be seen Cell a (matrix on the left) and Cell A (matrix on the right) differ in that there is no main effect of closeness on lucky feeling for win-outcome participants. However, for win-outcome, high-PGL participants, higher closeness is associated with a decrease in lucky feeling. These plots primarily demonstrate that personal luck beliefs enhance the main effects. In particular, the relationship of closeness to lucky feeling for winners is not present for the whole sample, but is for the high-PGL median-split of the sample. Again, these are stylised illustrations, intended to ease comprehension of these results, which are the effects on outcome congruent luck feelings of the three-way interaction of outcome, closeness and outcome-congruent luck belief. The matrix to the right will be carried forward to the chapter discussion below.

The third key finding is that outcome-congruent luck feelings are the 'active' predictor of risky choice. The pattern of results is consistent with an activation model of luck feelings. That is, regardless of the luck feeling—lucky or unlucky—risky choice

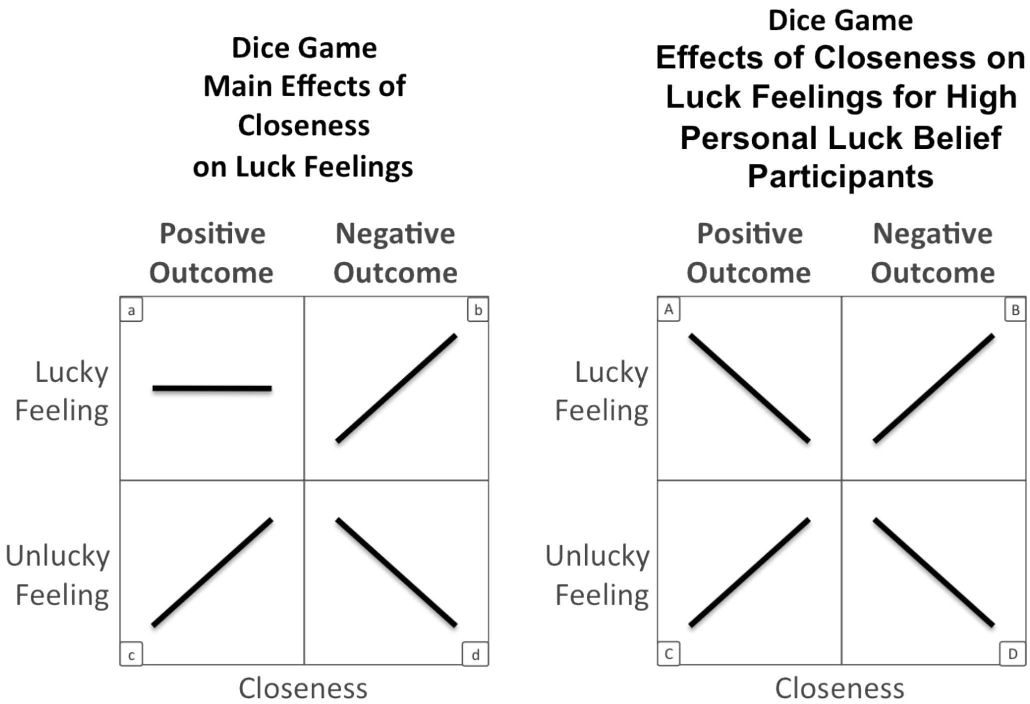

Figure 5.11: Stylised Illustrations of luck feelings and closeness by Outcome - Eight plots of the relationship of closeness and luck feelings. Along the x-axis is closeness, along the y-axis are two types of luck feelings. The relationship of lucky and unlucky feelings by game outcome is stylised by a line slope for easier comprehension; not all slopes are actually equal. The matrix to the left is for the main effect for closeness on the two types of luck feelings. The matrix to the right also plots the effect of closeness on the two types of luck feelings, but only for high (congruent) personal luck belief participants. In the case of lucky feeling, the congruent personal luck belief is PGL. In the case of unlucky feeling, the congruent personal luck belief is PBL. Positive outcome refers to winning. Negative outcome refers to losing. Note that cells are labelled with unique identifiers.

increases monotonically with luck feeling. Unlucky feelings are relatively unstudied in the literature, compared to lucky feelings. Intuitively, it is compelling that they should highly negatively correlated; opposites. They clearly have not been demonstrated to be so in this study. Rather, unlucky feelings appear to operate more or less independently of lucky feelings. Lucky and unlucky feelings are not two sides of the same coin. They are instead two different currencies; fiat according to outcome. A lucky feeling for win-outcome participants led to more risky choice consistent with a 'hot-hand' fallacy. Namely that a win was followed by putting more at stake in the following round. An unlucky feeling for loss-outcome also led to more risky choice, but their behaviour was consistent with a gambler's fallacy explanation. Namely that a loss was followed by putting more at stake in the following round.

5.7 Chapter Discussion

The first aim of this chapter was to explore the impact of an experimental manipulation of prospective-type luck feelings. Have I actually manipulated prospective-type luck feelings in this study? One argument that I have done so relies on the exact mismatch of my findings to those from the numerous studies by Teigen. Had I manipulated retrospective-type luck feelings, I would anticipate a replication of the findings of Teigen. Another argument that I have manipulated prospective-type luck feelings rests on the face validity of the task. I did not ask participants to recall significant life events. Instead, participants played a game of chance, with some elements of control (they could choose the number and the dice they rolled), and the questions were clearly related to gambles.

The final aim of this chapter was to test the expanded general model of luck feelings in such a way that the results could be communicated in an elegant and easily interpreted manner. Relative to the difficultly of the task, I hope the reader will agree that this final aim has been met. The findings from the PLS analyses extend the current understanding of the antecedents of prospective-type luck feelings on risky choice. Those findings can be organised into three different themes that relate to three of the chapter aims described in the introduction on page 193. The first theme is related to the second aim of this chapter, which was to continue an examination of the counterfactual closeness hypothesis. The second theme from the PLS models is related to the third aim of this chapter, which was to examine the role of luck beliefs as moderators of prior outcomes and lucky feelings. The third theme from the PLS models is related to the fourth aim of this chapter, which was to investigate the influence of luck feelings on different types of risky choice. Each of these themes are discussed below.

5.7.1 Study Results Challenge the Counterfactual Closeness Hypothesis

The counterfactual closeness hypothesis has been thoroughly tested in the study presented in this chapter. The findings from this study are exactly the opposite of the predictions of the counterfactual closeness hypothesis. In Figure 5.12 I present a comparison of the right-hand matrix from Figure 5.11 with the predictions of the counterfactual closeness hypothesis. The stylised illustrations show clearly the differences manifest across each matrix. According to the counterfactual closeness hypothesis, a close-win should result in higher lucky feelings, relative to a far-win (Cell 1) because one can more readily imagine having lost. Also according to the counterfactual closeness hypothesis, a close-loss should result in higher unlucky feelings (Cell 4), relative to a far-loss, because one can more readily imagine having won. Although the counterfactual closeness hypothesis has not to my awareness been formally extended to outcome non-congruent luck feelings, the extrapolations are logical. A close-win should result in lower unlucky feelings (Cell 3), and a close-loss should result in lower lucky feelings (Cell 2). These are not merely the assertions of a counterfactual closeness hypothesis, but of Norm Theory (Kahneman & Miller, 1986).

Recall the quintessential demonstrations of Norm Theory: the person who misses a plane by 5 minutes, as compared to the person who misses a plane by 30 minutes; and the person who holds a lottery ticket only a few numbers away from the winning number, as compared to the person who holds a lottery ticket that is not close. Relative to the far misses, the close-misses would usually be considered to result in greater regret, frustration, and feelings of being unlucky. The findings from the present study should be somehow reconciled with the prior findings that support Norm Theory and the counterfactual closeness hypothesis. Either the two phenomena are unrelated, my results are misleading, or an alteration to the theory is required. I will attempt the latter of these. It is not lightly that I propose the counterfactual closeness hypothesis be augmented, and as such I defer a full discussion of this to the final chapter.

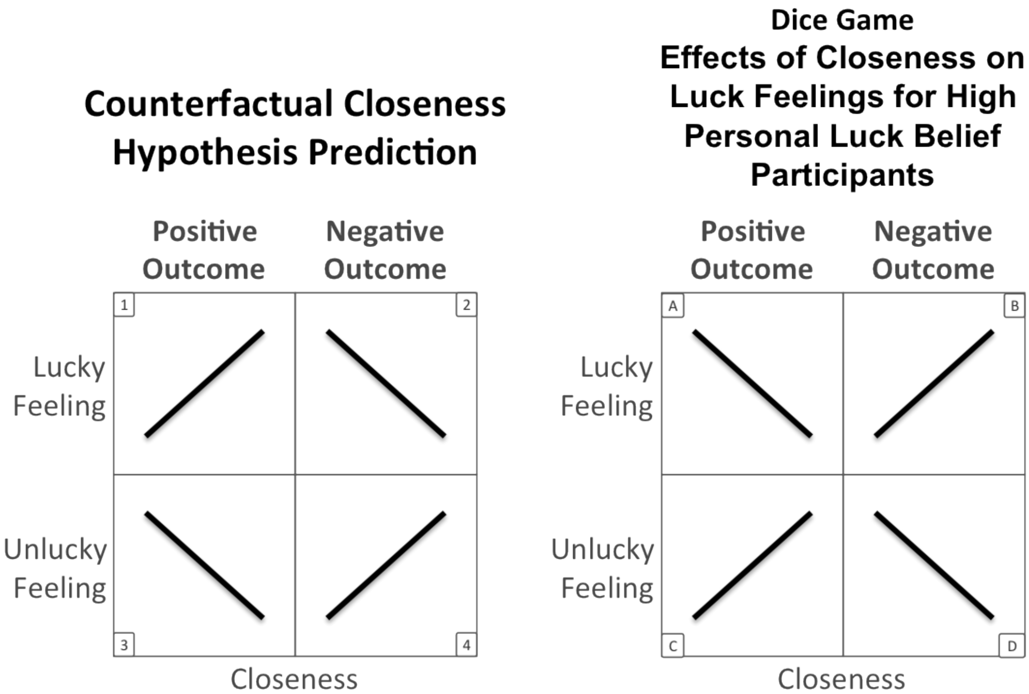

Figure 5.12: Lucky Feelings and Closeness, Prediction versus Finding - Presented are eight stylised relationships of Closeness and luck feelings. The matrix on the left hand side illustrates predictions from the counterfactual closeness hypothesis. The matrix on the right hand side illustrates actual findings from the dice game experiment. Along the top row are predictions and findings for lucky feelings by either positive outcome or negative outcome. Along the bottom row are predictions and findings for unlucky feelings by either positive or negative outcome. Note that each cell of the matrices has a unique identifier in the corner.

5.7.2 The Moderating Role of Luck Beliefs

Luck beliefs moderate the relationship between closeness and luck feelings. Table 5.11, which presented R^2 values and Cohen's f^2 metrics for various alternate model compositions, was illustrative. For loss-outcome participants, the interaction of outcome congruent luck belief and outcome congruent luck feeling had a Cohen's f^2 of only 0.03. For win-outcome participants, the interaction of outcome congruent luck belief and outcome congruent luck feeling had a Cohen's f^2 of 0.07. Both of these are quite low, but paths from the interaction term to the outcome congruent luck belief were statistically significant for both outcomes. The incremental variance explained by these interaction terms was 2% (losers) and 5% (winners).

Luck beliefs, together with the interactions had quite different explanatory power across the two models though. For win-outcome participants, the Cohen's f^2 was very high, 0.48 for the outcome congruent luck feeling. For loss-outcome participants, it was considerably lower, at 0.16. For the outcome non-congruent luck feeling, the metric was 0.06 and 0.31 for winners and losers respectively. Such a high metric (0.31) for the loss-outcome participants indicates that PGL had a large contribution to the lucky feelings: again suggestive that PGL could buoy lucky feelings in the face of an adverse outcome. Closeness also had quite different explanatory power across the two models. It explained virtually no unique variance in LN2 for winners, and little more unique variance in ULN2 for losers. Variance explained was about equivalent across the two luck feeling measures for loss-outcome participants.

The path differences across outcome groups that were presented in Table 5.12 support the conclusions illustrated in Figure 5.11. There were significant differences for the path from Close to ULN2 and there was also be a significant difference for the path between Close and LN2. The path from the interaction of PGL*Close to LN2 also differed across the two outcome groups, although the path from PBL*Close to ULN2 did not.

5.7.3 Relating Luck Feelings and Risky Choice

Luck feelings influence risky choice in a symmetric manner for amounts gambled, and in a unique manner for ambiguity tolerance. Outcome-congruent luck feelings have the same effect on risky choice generally for either outcome. Lucky-feeling winners on average could be expected to risk a nearly equivalent amount in a lottery gamble as unlucky-feeling losers. I expected the unlucky feelings of losers to be associated with a reduction in risk. Perhaps this finding is consistent with the view that a luck feeling is an 'activation', as was concluded from the previous study. Gamble confidence was positively related to outcome non-congruent luck feeling for both winners and losers, though the variance in that item was questionable, with a high modal response of 50% (confidence). I am less confident in this result, even though the pattern holds across both outcomes.

One type of risky choice was most strongly affected by lucky feelings for those experiencing any outcome: ambiguity tolerance for winners. The β value for the path from LN2 to Ambig in the winners model was 0.353 and the R^2 value was 12.4%. Although the variance explained is not exceedingly large, it argues that the intuitively compelling assertion that lucky feelings should influence risky choice is most accurate where it concerns certainty, and not quantum of risk. Feeling lucky had the strongest effect on moving participants toward gambles with unknown odds, versus gambles that with known odds. There were also effects on the amount of risk taken, as operationalised by a hypothetical gamble of minutes, and an amount invested in a lottery. However, these effects were smaller and had less variance explained, respectively, about one-quarter and one-half of that explained in the ambiguity construct.

5.8 Limitations

In hindsight, there are design aspects of the study that could be improved. One in particular is the inclusion of an affect measure after the game outcome. This would allow for a direct measure of the role of affect in prospective-type lucky feelings. I made the decision to drop the measure of affect following the pilot study because I felt that the effects of the manipulation might extinguish after extended surveys. I made it a priority to manipulate luck feelings, and test the system of luck beliefs, closeness and outcome in the prediction of luck feelings, which in turn might predict risky choice. Having established an understanding of this system then, further studies can assess affect as an alternative explanation in a more focused manner.

There are of course the validity concerns attendant with using undergraduate psychology students as subjects, and with not using monetary incentives. There is also the concern regarding the use of risky choice measures that were hypothetical in nature. It could be asserted that hypothetical questions might generate responses that did not correspond to real decision making behaviour. The "effort-model of decision making" (Smith & Walker, 1993) argues that payoff size should attenuate irrational biases in real decisions due to increased cognitive effort vis-a-vis the incentive. However, past research has shown that hypothetical gambles do not differ markedly from real ones, even for gambles that have real payoffs of up to 50 USD (Kühberger, Schulte-Mecklenbeck & Perner, 2002). The findings indicate the manipulation was effective in altering luck feelings and risky choice, after taking into luck beliefs. Whether hypothetical decision making in this study led to an attenuation or exaggeration of response cannot be known without further research.

Another experimental design feature that could be improved is to remove the consequence of the game outcome. It is possible that the different outcomes for participants led to the responses. This is actually what was intended, but I recognise that some might view the different outcomes as a confound to the results. Certainly, the alternative to this approach is of interest. That approach was demonstrated well in the study by (Wohl & Enzle, 2003), where only the counterfactual outcome differed and all participants received the same prize. A study conducted in my lab addressed this question. In an honours thesis recently submitted by a student in my lab (Li, 2011), no prize was offered apart from the satisfaction of winning the game. Results from that study indicated that the prize of leaving early in unimportant to influence luck feelings and risky choice responses.

Another possible concern that some might have with these findings is that they are based on PLS models, with limited corroboration from more traditional statistical techniques conducted in Sections 5.4 and 5.4. In order to further compare the results of the PLS models for winners and losers with those generated in a more traditional analysis, Table 5.13 presents the correlations of luck feelings variables with risky choice. The top matrix is for loss-outcome participants and the bottom matrix is for win-outcome participants. The bolded terms in the model are the average of constituent items for a given construct (e.g., Mins = average of DG_Mins and CG_Mins). The intercorrelations of risky choice variables are also provided in that table.

For loss-outcome participants, the results of PLS and the correlations presented in Table 5.13 are in general agreement with respect to Mins and LG. The measures for

Conf failed to reach statistical significance in the correlation matrix. For win-outcome participants, the results are in general agreement with respect to LG, Ambig and Conf. However, the measures for Mins failed to reach statistical significance in the correlation matrix. The differences are not sufficient to threaten conclusions from the PLS results.

From an operationalisation perspective, one of the more important limitations relates to measurement of luck feelings. Luck feelings were measured with two items – one for lucky feeling and another for unlucky feeling. These two items were repeated, once prior to the manipulation and once after the manipulation. The single-item nature of the lucky and unlucky feeling measures provides no insight into the reliability of the measures, and cannot be compared directly to the luck composite measure from Chapter 4. The repeated nature of the measure, whilst potentially providing information on the change in luck feelings across the manipulation, leaves open the possibility of hypothesis guessing on the part of participants.

In relation to protocol, another limitation is that participants were run in large sessions with game outcomes of others clearly announced. This may have led to demand characteristics where participants were aware of not only their own, but others outcomes, and made counterfactual assessments and how they should respond to the dependent variable items. Moreover, hypotheses were known by all experimenters, which may have introduced a subtle, albeit unintentional bias.

To put these threats in context however, recall that luck believing winners and losers showed on average greater risky choice, relative to non-believing winners and losers. Thus, on average winning and losing had a similar influence on outcomes for all members in a session – any intra-session biases did not play out to have an effect as participants in a session were either all high luck belief or all low luck belief. I note that the finding that high luck belief loss-outcome participants would take on more risk was a surprising finding, contrary to initial expectations of experimenters, so any effect arising from experimenter bias would have been present only for luck-believing winners.

A final limitation is that there was social interaction between participants before, during and after the dice game manipulation, and these participants probably held similar luck beliefs. Thus, what I may have interpreted here as an individual-level phenomenon may in fact be a social one, or the result of a mix of social and individual influences.

Loss-Outcome Participants

	1	2	3	4	5	6	7	8	9	10	11	12
1 LN2	1	–	–	–	–	–	–	–	–	–	–	–
2 ULN2	–	1	0.22	–	0.26	–	–	–	0.23	–	–	–
3 **Mins**	–	0.22	1	0.95	0.95	–	–	–	0.26	–	–	–
4 DG_Mins	–	–	0.95	1	0.81	–	–	–	0.25	–	–	–
5 CG_Mins	–	0.26	0.95	0.81	1	–	–	0.26	0.25	0.26	–	0.22
6 **Conf**	–	–	–	–	–	1	0.94	0.91	–	–	–	–
7 DG_Conf	–	–	–	–	–	0.94	1	0.71	–	–	–	–
8 CG_Conf	–	–	–	–	0.26	0.91	0.71	1	–	–	–	–
9 LG	–	0.23	0.26	0.25	0.25	–	–	–	1	–	–	–
10 **Ambig**	–	–	–	–	0.26	–	–	–	–	1	0.79	0.74
11 Balls_2	–	–	–	–	–	–	–	–	–	0.79	1	–
12 Balls_3	–	–	–	–	0.22	–	–	–	–	0.74	–	1

Win-Outcome Participants

	1	2	3	4	5	6	7	8	9	10	11	12
1 LN2	1	–	–	–	–	–	–	–	0.27	0.35	0.25	0.28
2 ULN2	–	1	–	–	–	0.25	0.26	–	–	–	–	–
3 **Mins**	–	–	1	0.89	0.91	0.28	–	0.31	0.35	–	–	–
4 DG_Mins	–	–	0.89	1	0.61	0.25	0.22	0.22	0.29	–	–	–
5 CG_Mins	–	–	0.91	0.61	1	0.26	–	0.33	0.34	–	–	–
6 **Conf**	–	0.25	0.28	0.25	0.26	1	0.9	0.87	–	–	–	–
7 DG_Conf	–	0.26	–	0.22	–	0.9	1	0.57	–	–	–	–
8 CG_Conf	–	–	0.31	0.22	0.33	0.87	0.57	1	–	–	–	–
9 LG	0.27	–	0.35	0.29	0.34	–	–	–	1	–	–	–
10 **Ambig**	0.35	–	–	–	–	–	–	–	–	1	0.77	0.75
11 Balls_2	0.25	–	–	–	–	–	–	–	–	0.77	1	–
12 Balls_3	0.28	–	–	–	–	–	–	–	–	0.75	–	1

Table 5.13: Correlations of LN2 and ULN2 with Risky Choice Variables - Correlations are significant at the $p < .05$ level. Bolded terms are the averaged scale of respective variables, which correspond to the constructs used in the PLS analyses.

5.9 Chapter Summary

The preliminary analyses in Section 5.4 found that subjective perceptions of game closeness were linearly related to objective measures of game closeness, thus closeness could be compared directly against the two objective measures of closeness, RD and RD3, as an antecedent of luck feelings. The preliminary analyses also established some confidence in the experimental manipulation through the use of a measure of attributions to skill, luck, and chance to the game. Finally, the preliminary analyses established that personal luck beliefs and game outcomes do not need to modelled as antecedent to closeness. Closeness was unrelated to game outcome and all luck beliefs, and also unrelated to luck attributions, taking into account game outcomes.

In Section 5.5, game outcome, closeness and the interaction of game outcome and closeness had no direct effect on any risky choice variables, although luck feelings were responsive. However, only unlucky feelings were responsive to the interaction of game outcome and closeness; lucky feelings were not. This is a failure to support the counterfactual closeness hypothesis. Outcome congruent luck feelings were much more responsive to game outcome, relative to outcome non-congruent luck feelings. Closeness was found to be associated with lucky and unlucky feelings to about the same extent. An interaction with game outcome explained only a small amount of additional variance in unlucky feelings, and no additional variance in lucky feelings. Testing the three-way interaction of game outcome, outcome congruent luck belief and outcome congruent luck feelings emerged as the next logical step to take. All luck beliefs were positively associated with both luck feelings. It is surprising that PGL would positively associated with unlucky feelings, and that PBL would be positively associated with lucky feelings. It was suggested that perhaps this is artifactual, with PGL and PBL covarying positively with GBL and therefore with each other. These findings provided insight and confidence to the general model (presented in the introductory paragraphs to this chapter) that was then tested in Section 5.6.

In Section 5.6 the general model of this chapter was demonstrated to be explanatory of the phenomena of interest: the influence of luck feelings on risky choice, and the antecedents to luck feelings. Luck feelings differ by game outcome in their ultimate influence on risky choice, but interestingly both lucky feelings and unlucky feelings may share a common feature: activation. The outcome congruent luck feeling was associated with risky choice variables for both winners and losers. Luck beliefs moderate outcome and luck feelings, but predominantly in an outcome congruent fashion. For winners, PGL moderates outcome to influence lucky feelings, which then act on risky choice. For losers, PBL moderates outcome to influence *un*lucky feelings that then acts on risky choice. Ambiguity tolerance was unique among the risky choice constructs in so much as it was only predicted by the lucky feelings of winners, and it was the most strongly predicted construct of all risky choice variables for both winners and losers. When one thinks of lucky feelings influencing risky choice, ambiguity tolerance is surely archetypal.

Chapter 6

General Discussion

6.1 Chapter Introduction and Overview

This chapter is presented in three main sections. The first section evaluates the principal methodological and empirical contributions of this thesis against the research issues developed in Chapter 2. The second section proposes a theory, the *Activation Theory of Luck Feelings* (ActLF), which attempts to integrate prior empirical findings and theoretical literature with the results reported from the studies in Chapters 4 and 5. The final section provides a summary of the thesis.

6.2 Contributions of the Thesis

The literature on the influence of lucky feelings in decision making involving risk and uncertainty is relatively small, compared to many other areas of psychology. Only four papers were identified which were specifically relevant to an examination of the relationship of luck feelings and risky choice. A number of other prominent studies—mostly by Teigen, Wagenaar and Keren—provided a broader foundation for the understanding of common conceptions of luck. Six research issues were identified in Chapter 2 and summarised from page 53 to 59. These research issues provided direction for the body of work that led to this thesis. An evaluation of the contributions of the thesis to the various research issues identified is provided now.

6.2.1 Luck Beliefs

The first and most fundamental issue was the measurement and dimensionality of belief in luck. The earliest theorising on luck identified luck belief as a factor to take into account when considering luck feelings and their impact on decision making (Cohen, 1960). Much later, Darke & Freedman (1997a) published the first broadly accepted measure of luck beliefs, the 12-item Belief in Good Luck Scale. Approximately a decade later Maltby et al. (2008) revised that original scale, proposing 22 items. Twelve of these were nearly verbatim from the original 12-item scale. The original scale was thought to contain only a single dimension, although the revised scale found four. Issues that arose from the comparison of these two scales focused on the dimensionality of luck beliefs and the composition of the items to measure those dimensions. Other issues emerging from the literature were the use of the 12-item scale as a dependent variable in Wohl & Enzle (2002) and Wohl & Enzle (2003). A further issue in the context of the present thesis was which luck belief dimensions to use in modelling the effects of a prior outcome on luck feelings.

Chapter 3 refined these prior measures to form the *16-item Belief in Good Luck Scale* (BIGL16), a scale that measures four dimensions of luck beliefs. Using a combination of factor analyses and PLS modelling, the items were demonstrated to have both convergent and discriminant validity, and the dimensions were demonstrated to have nomological validity. Most importantly, a structural arrangement of the luck belief dimensions was found that should assist in selection of particular dimensions for particular purposes. For example, if one is interested in explaining the origins of luck beliefs in general then the focus should be toward the constructs of Luck is Random (LIR) and General Belief in Luck (GBL). However, if one is interested in explaining the impact of outcome congruent luck feelings on risky choice then the focus should be on the two personal luck beliefs, Belief in Personal Good Luck (PGL) and Belief in Personal Bad Luck (PBL).

The BIGL16 differs from the scale proposed by Maltby et al. (2008) in two important ways. Firstly, the BIGL16 is a more parsimonious and coherent scale. Items with questionable content validity have been removed, and the factors are more unitary as a result. A compelling structural arrangement was established in Chapter 3. Moreover, results from the validation exercise support and extend a previous finding—that the dimensions of *Luck is Random* and *General Belief in Luck* are differentially related to cultural background. A further three constructs were found to be related to more than one luck belief dimension and are likely to be fruitful foci for future research: intelligence, superstitious beliefs, and understanding of randomness. The personal luck belief dimensions were carried forward to two studies in Chapters 4 and 5 that supported previous findings that luck beliefs are important moderators of luck feelings and choice behaviour. Most notable of these findings was that a belief in personal good luck (PGL) moderated a luck composite scale and overestimation; and that PGL and PBL act in an outcome-congruent manner in relation to the general model of luck.

6.2.2 Measurement of Luck Feelings

Another prominent issue was the measurement of lucky feelings as a predictor of risky choice. Wagenaar & Keren (1988) used a discriminant analysis that distinguished chance from luck. They found that participants tended to describe lucky stories using phrases like ‘escape from negative consequences’, ‘prolonged consequences’, ‘accomplishment’, and ‘luck’. No measures of luck feelings have previously taken into account these descriptive phrases in the measurement of luck feelings.

In Chapter 4 I created a luck composite that reflected the findings of Wagenaar & Keren (1988), and in large part also is philosophically aligned with Teigen’s approach. The composite demonstrated good internal consistency in the sample I used, most notably in the post-manipulation measures. There were four items that comprised the composite—lucky, fortunate, relieved, and successful. These were found to belong to a single factor, but were not found to be individually predictive of dependent variables. The items were also not individually predicted by the manipulation. As a four-item construct however, they performed quite well, with significant variance in the construct score being explained by PGL, positive affect and negative affect. The luck composite construct predicted overestimation both before and after the trivia-task. The construct was also used in an interaction term (with PGL) to predict overestimation. The luck composite proposed in Chapter 4 was demonstrated to be an important element of a larger model, and thus a degree of nomological validity was afforded to it.

Only a single paper has previously asked a direct measure of luck feelings in a test of decision making (Jiang et al., 2009). Two others have used the BIGL12 as a dependent variable of a luck manipulation (Wohl & Enzle, 2002, 2003). Whether these qualify as measures of lucky feelings is doubtful—the authors do not assert they do in any case. Rather, they describe the measure as one of the 'personal deployment of luck'. (Later Wohl et al. (2011) propose a scale more in line with this conceptualisation, the Personal Luck Usage Scale.) From a face validity perspective, a direct item asking about lucky feelings (i.e., "How lucky do you feel right now?") seems an appropriate measure to use. However, no previous research has examined the relationship of feeling lucky to feeling unlucky. Nor has the pattern of influence of the two luck feelings on risky choice been investigated.

The study reported in Chapter 5 used a direct measure of lucky feelings, and also a direct measure of unlucky feelings. These measures demonstrated good predictive validity in a model that included various risky choice dependent variables. The direct measures of luck feelings were also found to be related to a number of independent variables, including the experimental manipulation. Lucky and unlucky feelings were most certainly found to not be simply the inverse of one another, as evidenced by their relatively low correlations for both win-outcome and loss-outcome participants. Rather, the results of this study suggest that lucky and unlucky feelings have the same influence on risky choice when a prior outcome is taken into account. (This 'congruence' relationship of the two luck feelings is discussed further below.)

Taken together, findings from the studies from Chapter 4 (which used the luck feelings composite measure) and Chapter 5 (which used the two direct luck feelings measures) provide a foundation for further exploration of the nature of luck feelings and their relation to other variables of interest. One notable limitation of the studies is that they do little to compare retrospective-type luck feelings against prospective-type luck feelings. There is very little that can be said of their relation to each other, nor of their differential prediction of risky choice variables, including overconfidence. These unanswered questions stand out among the limitations of this thesis. The thesis has however, addressed the first principles of these questions, which is to develop the measures sufficiently so that comparisons can be readily undertaken in future studies.

6.2.3 Affect and Luck Feelings

Another issue that was identified was the role of affect in luck feelings, and in the influence of luck feelings on decision making. Past work on luck feelings has questioned the role of affect, with mixed results. Wohl & Enzle (2003) found no effect of their luck manipulation on a sad/happy feeling item. Jiang et al. (2009) however, found that happiness was higher in their lucky condition and lower in their unlucky condition. These two studies used different types of manipulations. The former used a wheel-of-fortune, whereas the later used a subtle priming manipulation. This could be one reason for the mixed findings. However, the items used to measure affect in both of these studies did not conform to recommendations regarding measurement of affect (Watson et al., 1988). A further test of affect was desirable, to clarify issues pertaining to measurement and these mixed findings.

The measures of positive and negative affect that were used in the study reported in Chapter 4 conformed to those recommended by prominent affect researchers. Despite this, there remains some question as to the relation of affect to luck feelings. Both positive and negative affect were found to mediate a prior manipulation and the luck composite. However, the variance in the luck composite explained by the experimental manipulation alone was small, as was the variance explained in the positive and negative affect constructs by the experimental manipulation. So although there was complete mediation of the effect of the manipulation on the luck composite, the absolute effect was quite small overall. Arguing for a distinction of affect and luck feelings, only the luck composite was predictive of overestimation. Perhaps the most that can be said is that affect and lucky feelings are 'distinct but overlapping'? The very nature of luck feelings, described in the first chapter indicate this *should be* the case. The precise configuration of luck feelings (both retrospective-type and prospective-type) to affect, emotion, and mood would probably be advantaged by assistance from researchers in the areas of affect, emotion and mood given their nuanced understanding of the key distinctions among these states of being.

Insights regarding the relation of affect and luck feelings to each other and risky choice are limited to the luck feelings composite and two measures of overconfidence. Affect was not included in the study reported in Chapter 5 because of more pressing concerns to capture what was thought would be rapidly extinguishing effects of the manipulation on risky choice. Having developed some confidence in the primary relationship of luck feelings and risky choice, an expansion of future research to extend the affect-investigation to direct measures of luck feelings and risky choice variables. One immediately apparent future study would include affect in the models tested in Chapter

4, testing for mediation in a way similar to the model in Figure 4.6 (page 170). Another future study would test for differential prediction of risky choice variables used in Chapter 5 by affect and direct measures of luck feelings.

Despite silence regarding the influence of affect on direct measures of luck feelings and on risky choice, this thesis establishes the importance of using widely accepted measures of affect in future research. The findings herein also provide a foundation for further studies of affect vis-a-vis retrospective-type and prospective-type luck feelings.

6.2.4 Dependent Variables and Experimental Manipulations

Two further issues regard the selection of dependent variables and experimental manipulations. Risky choice measures to date have been confined to gamble amounts and confidence in gambles (Darke & Freedman, 1997b; Wohl & Enzle, 2003). A related measure, product evaluation, has also been used but was questionably related to risk (Jiang et al., 2009). Several manipulations of lucky feelings have been used, but none of these has produced a result that directly related lucky feelings to risky choice. The most common manipulation has been a vignette-based approach, such as those by Wagenaar & Keren, and Teigen. In the main, these have required subjects to make subjective judgements regarding the response of a fictional character to a particular experience. More recently a protocol has been used with increasing frequency, whereby participants experience an outcome of a game of chance (Darke & Freedman, 1997b; Wohl & Enzle, 2003). Whether these give rise to the same type of lucky feelings (i.e., lucky-gratitude and lucky-expectancy) remains an open question. More importantly, the relation of luck feelings and risky choice has not be established.

The studies herein provided two different manipulations of luck feelings and two broad sets of decision making variables. In Chapter 4 a manipulation consistent with retrospective-type luck feelings was used and tested against two types of overconfidence. In Chapter 5 a manipulation consistent with prospective-type luck feelings was used and tested against a number of risky choice variables. Of course, not every study can address every issue at once. These studies represent only two cells in a 2x2x2 matrix of experimental manipulation (retrospective versus prospective), luck feelings measure (luck composite versus direct measures), and dependent variable (overconfidence versus risky choice). There may be other types of dependent variables that are of interest to a particular context or research. The full investigation of these eight cells in this matrix could occupy a curious researcher for many years, not including the many further insights that illuminate other as-yet-unknown directions.

Despite this thesis providing only a partial picture of the whole field of enquiry, there are important and substantial insights that can guide future research, and perhaps even inform past research (as I will discuss in the ActLF theory proposal). One of the more interesting of those insights is the general model of luck feelings presented in the beginning of Chapter 5. That general model combines three established antecedent factors to luck feelings, and specifies the mediation of luck feelings between those factors and risky choice. Each of the antecedent factors has been previously examined, but none together at once. Expanding the model to include both lucky and unlucky feelings, as well the two personal luck beliefs provides a comprehensive model that can be subjected to further empirical enquiry. The model is built on a conceptual foundation, and was successfully tested in the context of a competitive game of chance. Whether this model holds in other contexts remains an open question, but the general model can serve as a guide for operational-level theory.

Arising from that general model is the application of the concept of congruence. Congruence greatly simplifies the general model so that win- and loss-outcomes can be compared more directly. Congruence stipulates that a positive outcome has an influence on risky choice via a lucky feeling, and closeness is moderated by a belief in personal good luck. For a negative outcome, the influence on risky choice operates via an unlucky feeling, and closeness is moderated by a belief in personal bad luck. It is the outcome that determines the relevant constructs in the general model of luck. That said, luck feelings do not appear to substantially mediate antecedents of luck feelings and risky choice, giving rise to further investigation of the boundaries in applying the congruence concept. Regardless, further investigation is recommendable and more consequently more easily framed using the congruence vernacular.

Findings in relation to luck feelings and risky choice are among the most important and novel of any emerging from this thesis. These have been discussed at length in respective chapters. Of those previously discussed, two stand out. The first is that both lucky and unlucky feelings appear to be positively related to amounts invested in a gamble. The second is that ambiguity tolerance is influenced by lucky feelings arising from a positive outcome, and are not influenced by an unlucky feeling. In this respect, ambiguity tolerance appears to be a special case of risky choice as it relates to luck feelings and prior outcomes. Perhaps ambiguity tolerance is an exemplar type of risky choice vaguely referred to within lay conceptions of luck feelings?

6.2.5 A Holistic View of Luck Feelings and Decision Making

Another issue I addressed throughout this thesis was the constrained understanding of luck feeling phenomena in respect of the possibilities that a modelling approach affords. Previous studies in the area of luck had used designs and analytical techniques that provided a piecemeal understanding of luck feelings and risky choice. Some studies focused on antecedents to luck feelings. Other studies focused on the impact of a manipulation on risky choice *inferring* luck feelings as a mechanism. Yet other studies examined luck beliefs as a moderator of a manipulation and risky choice. A holistic understanding that brings all of these together was lacking.

This thesis represents the pioneering use of PLS path modelling in the study of luck feelings. The complexity of the models made it difficult to conceptualise and analyse the entire system at once without the use of a modelling approach. The general model could not have been tested so efficiently without a modelling approach, and the system-level insights would have been difficult to communicate. The technique of PLS path modelling is new to the area of psychology, despite it being a well-accepted technique in other research areas that share important features with psychology. As demonstrated herein, latent constructs are well-aligned with psychometric considerations regarding the indirect measurement of important variables. Also demonstrated was the relatively easy inclusion of intermediating mechanisms useful to understanding causal pathways regarding thought, belief and action. The testing of moderation, even three-way interactions, was efficient. Moreover, the visual representation of theoretically prescribed arrangements of constructs was a key benefit of a modelling approach. Perhaps the idea of congruence would remain undiscovered without the use of PLS modelling?

6.2.6 Counterfactual Thinking

A final issue was the examination of counterfactual thinking as a core element of luck attribution and lucky feelings. The bulk of Teigen's work on the common conceptions of luck has lent impressive support for what I termed the *counterfactual closeness hypothesis*. According this hypothesis, comparisons of an actual outcome to an imagined counterfactual one should lead to a feeling of being lucky: The closer the outcome to a counterfactual possibility, the more lucky a person should feel (i.e., in the instance of a near-negative outcome). However, Wohl & Enzle (2003) did not find that counterfactual direction was a mediator of their experimental manipulation and self-perceived luck (i.e., the single item from the BIGL12 scale). Nor did counterfactual direction mediate their manipulation and gambling behaviour. No previous studies have manipulated counterfactual closeness and examined its relationship to risky choice. Thus, there is mixed support for the role of counterfactual thinking in luck feelings as they relate to risky choice, even though Teigen's evidence predominantly outweighs Wohl & Enzle in terms of sheer volume.

Emerging from a careful consideration of the etymology and the modern-day use of the word 'luck' was a theme regarding the antilogous nature of the term. Luck can convey either gratitude or expectancy. From a causal attribution standpoint, the former focuses on the unpredictability of an experienced outcome, whereas the later focuses on the predictability of a future outcome. Teigen's experimental paradigm customarily asked participants how a focal character would feel given a particular vignette construction that manipulated closeness and other relevant factors. The study in Chapter 5 and the studies by Wohl & Enzle took a different approach, which was to test the effect of a counterfactual manipulation on subsequent risky choice. Those counterfactual manipulations were outcomes experienced directly by participants and were not of a significant nature (i.e., neither important nor having prolonged consequences). This difference in experimental paradigm is perhaps an explanation for the differing results of Teigen's counterfactual closeness hypothesis. From a logical standpoint, it is unclear that a feeling of 'lucky-gratitude' (i.e., arising from near-death experience) *should* lead to increased risk taking. Nevertheless, a direct empirical test of this was lacking.

Although this had been discussed at length, it bears repeating at this point to introduce the following section. The findings from Chapter 5 were in direct contradiction to the predictions from the counterfactual closeness hypothesis. Rather than feeling luckier with closer outcomes (where an alternative would be more easily imagined), win-outcome participants on average felt luckier for far-wins. This contradiction held for negative outcomes as well. Rather that feeling more unlucky with closer outcomes (where an alternative would be more easily imagined), loss-outcome participants on average felt more unlucky for far-losses. The study reported in Chapter 4 found no effect on the lucky composite for counterfactual closeness above and beyond that of counterfactual direction alone.

Given the body of evidence generated by Teigen to support the counterfactual closeness hypothesis, the onus is on me to explain my findings as either (1) a failure to replicate his findings, (2) an instance of my results measuring a substantially different luck feelings type, or (3) compatible with Teigen's work in a larger or alternate theoretical system. It is the latter of these three that will be attempted in the next section.

6.3 A Theory of Luck Feelings

The theory proposed below is speculative in nature. The theory fits to previous findings, including those that came before this thesis. The theory also fits to common sense and previous theorising. This should not be confused with the theory having withstood tests of predictions it makes in an *a priori* fashion. The theory does have testable propositions though, and these may guide further investigation of luck feelings and associated phenomena.

6.3.1 Brief Introduction to the Activation Theory of Luck Feelings (ActLF)

There were primarily two findings that triggered a restructuring of the explanatory system of luck feelings. Firstly, I expected closeness to be related to luck feelings in the pattern predicted by the counterfactual closeness hypothesis but found the inverse pattern. Secondly, I expected unlucky feelings to be negatively related to risky choice, but found the inverse pattern. From these findings, I reconsidered results of the studies I had conducted, converging on an explanation intimated (albeit inadvertently) as early as the first Chapter, and in more concrete form at the end of Chapter 4.

The elements of the theory are basic and few in number. There is a prior *expectation* and a *deviation* of an outcome from that expectation. That deviation gives rise to an *activation*, which then results in a *lucky feeling*. Which type of lucky feeling—retrospective or prospective—is contingent on whether respectively there is or is not a *reference shift*. The central tenets of the Activation Theory of Luck Feelings (ActLF) yoke luck feelings to activation, and activation to deviation from prior expectations.

These will be explained in greater detail below, but a brief characterisation may be useful now as an introduction to the full proposal below.

Given a prior set of expectations, an individual experiences an outcome as conforming to (or deviating from) those expectations to some degree. The deviation of an actual outcome from a prior expectation gives rise to an opportunity, or even requirement, to attend to the situation at hand. That attention may be implicit and non-conscious or it may be explicit and conscious. Regardless of the individual's awareness, the deviation leads to an activation, a heightened state of arousal if you will. The greater the deviation from prior expectations, the greater the activation.

An activation can then give rise to a luck feeling of either a retrospective or prospective nature. Which type depends primarily on two different factors. The first is the extent of the deviation. Within a normal range of events, a prospective-type luck feeling should result. However, when the deviation is so great that it triggers a reappraisal of the original expectation, a shift can occur whereby a new expectation comes into focus and the actual outcome is appraised against that new expectation. That new expectation is, of course, the counterfactual outcome. Attendant retrospective-type lucky feelings result from the comparison of the actual outcome to the counterfactual one.

The second factor that affects whether a reference shift will occur (and thus the type of luck feeling) is the personal consequence of the deviation and resultant counterfactual outcome. For deviations that have little personal consequence, there is little concern for counterfactual outcomes. However, for deviations from prior expectations that implicate important personal consequences, there is a much greater appeal for considering a counterfactual outcome that is better or worse. Holding all else constant, if an actual outcome approaches a life-altering counterfactual, the reference shift is more likely to happen.

Risky choice should be associated with prospective-type luck feelings in a way that is consistent with activation. To wit, both a lucky and unlucky feeling arise from activation, and mediate activation and risky choice. This would be especially so for individuals with a strong belief in luck. Metaphorically, one might view the activation as a form of energy potential that is converted to a kinetic form in a future decision involving risk. Continuing the metaphor, when activation triggers a reference shift, the potential energy is converted to a kinetic form in the reframing of the reference point from an original expectation to a counterfactually worse or better outcome. A feeling of relief or regret may then occur but is unassociated with risky choice in a direct manner. Instead, feelings of regret and relief are only related to risk taking in future trials in the same domain as the deviation occurred; a form of learning.

I now lay out the theory as a series of explicated formal statements, beginning with a discussion of the objectives of the theory and concluding with a discussion of some testable predictions.

6.3.2 Objectives and Impetus for a Theory of Luck Feelings

The challenges of presenting a comprehensive theory of luck feelings are considerable. A theory of luck feelings should integrate both retrospective-type and prospective-type luck feelings; the former being characterised by a feeling of relief or regret, the later by a feeling of expectancy regarding a future event. A theory of luck feelings should also include three antecedents that recur across numerous studies in the area of luck: prior outcomes, luck beliefs, and counterfactual closeness. As regards counterfactual closeness, a theory of luck feelings should account for past (strong) support for the counterfactual closeness hypothesis, and my findings in Chapter 5 that are in opposition to the predictions from the counterfactual closeness hypothesis. A theory of luck feelings should parsimoniously handle the different valences of luck feelings (i.e., lucky and unlucky) as well as the different dimensions of luck beliefs (i.e., PGL, PBL, and possibly GBL). Finally, a theory of luck feelings should predict when, and to what extent, risky choice will arise from luck feelings. In the interest of clarity, I restate these objectives in list form.

A comprehensive theory of luck feelings should:

- Integrate retrospective-type and prospective-type luck feelings.
- Account for the known antecedents of luck feelings.
- Reconcile different findings regarding counterfactual closeness.
- Assimilate the two 'valences' of luck.
- Predict when, and to what extent, risky choice will arise from luck feelings.

Theoretical explanations of luck feelings are limited to date. The most prominent theorising has been concerned with the response of luck feelings to an imagined counterfactual outcome (Teigen, 1996). Based on Norm Theory (Kahneman & Miller, 1986), the counterfactual closeness hypothesis predicts that a more readily imagined counterfactual outcome (in relation to an actual outcome) will lead to stronger luck feelings. The counterfactual closeness hypothesis subsumes the larger proposition that counterfactual direction should be predictive of the direction of a lucky feeling. If one experiences an event (i.e., winning a lottery) and references it to an imagined worse outcome (i.e., losing the lottery), then one should feel lucky. This is, on the surface, a very reasonable proposition. It is also a proposition that is well-supported by repeated studies. Teigen's extensive programme of research on luck, has supported both the influence of counterfactual direction and closeness on estimates of the extent to which a vignette character should feel lucky. A recent study found that real survivors of near-death experiences do indeed feel lucky (Teigen & Jensen, 2011), just as would be expected from previous results. In relation to risky choice, Wohl & Enzle (2003) linked counterfactual direction (but not closeness) to amounts gambled, showing that the BIGL12 composite score was also responsive to the counterfactual direction manipulation.

There is no formal theory as to why a lucky feeling should give rise to risky choice. Perhaps the two constructs are considered by many to be definitionally linked. That is, 'feeling lucky' is a state of being that indicates intention toward risk taking. In this view, feeling 'unlucky' would be presumed to indicate an intention away from risk taking. However, results from the study in Chapter 5 argue against that presumption.

Darke & Freedman (1997b) was perhaps the first instance where luck belief was tested as a moderator of a prior event and some form of risky choice. For them, a lucky feeling was related to the prior outcome, but no direct test of the lucky feeling on risky choice was reported. Combining Darke & Freedman with Teigen yields the three-way interaction of prior outcome, luck belief, and closeness in the prediction of luck feelings, which thus far has been assumed to be influential of risky choice. This is a descriptive theory of sorts, but does not contain elements of explanation as to what gives rise to luck feelings, and the mechanism that then results in some influence of luck feelings on risky choice. Nor does it fully account for the dimensionality of luck belief proposed by Maltby et al. (2008) and further refined in Chapter 3. There have been no studies that were concerned with unlucky feelings and how they might relate to lucky feelings.

There is support from the studies I reported earlier for the general model of luck feelings: that prior outcome, luck belief, and closeness combine in some fashion to give rise to luck feelings. However, the results reported in Chapter 4 suggest that counterfactual closeness does not predict luck feelings better than counterfactual direction. Even more concerning, Chapter 5 reported a study that found an opposite pattern to that anticipated from a counterfactual closeness hypothesis: closeness was inversely related to outcome-congruent luck feelings. Does the finding that closeness is inversely related to luck feelings challenge only the counterfactual closeness hypothesis, or does it also extend to counterfactual direction?

The most immediate explanation that reconciles my findings to those of Teigen is that retrospective-type luck and expectancy-type luck are qualitatively different. In other words, there could be two different luck theories; one dealing only with the former and another dealing only with latter. Recall that Teigen's work focused on retrospective-type luck feelings, while the study reported in Chapter 5 focused on prospective-type luck feelings. This is plausible, but insufficient as a comprehensive theory. It neither explains the difference between the two types, nor why they should respond differently to counterfactual closeness. Also concerning is that results from a counterfactual manipulation experiment in Wohl & Enzle (2003) are somewhat supportive of the closeness hypothesis: all participants landed on a small payoff in a wheel of fortune spin, but it was a near-big loss that resulted in higher gambles, relative to a near-big win.

6.3.3 Activation as an Origin of Luck Feelings

I sought a theoretical system that would explain the *origin* of both lucky-gratitude and lucky-expectancy. That search took me back to the results from the study reported in Chapter 4. At the conclusion of that chapter I presented a summary diagram (Figure 4.13) of the results. That summary characterised lucky feelings as an activation. I then returned to this activation-characterisation at the conclusion of Chapter 5. I suggested there that an activation account of luck feelings could explain the positive relationship that an outcome congruent luck feeling had with risky choice, irrespective of whether the feeling was a lucky or unlucky one. This idea of activation may prove a fruitful exercise in terms of theory development. To begin let's consider the first formal statement of the theory:

> **1) The deviation of an outcome from a previously held expectation results in an activation. The larger that deviation, the stronger the activation.**

Deviation from an expectation of any kind can capture attention and beckon explanation or interpretation. Imagine just now, if you looked up to see an elephant walking by your door. Unless your residence is in a zoo, this is probably a very rare and unexpected event. The more rare the event, the more notice you would take. Laying aside whether you perceive this particular pachyderm to be placid or pugnacious, your attention is captured and your reaction is probably to follow-up with an enquiry as to firstly why there is an elephant in your hallway, and secondly what it might portend for you? Playing a dice game, participants must surely have had no expectation of a large win or large loss, but rather, that the dice game could easily go to either player. In the instance of a close game, participants on average reported a lower level of outcome-congruent luck feeling: it did not violate an expectation, and therefore the outcome did not lend itself to any great degree of interpretation. This close outcome may be equated with needing an explanation for having arrived safely at work this morning. It is unsurprising and therefore goes unnoticed.

However, a far-win or a far-loss beckons explanation and interpretation. This is because it violates a central assumption about what one could expect. This accords with Kansas-Lottery-winning Ms Ott's receiving two cans of soda and two bags of chips, having paid for only one of each. Had she received only one of each, she would not have felt lucky, would not have bought a lottery ticket, and would not have won. (Though perhaps, she would have found something else to feel lucky about instead, if she was inclined to buy a lottery ticket anyway.) I reiterate though, this activation is not restricted to only the domain of happy surprises. Recall that on average, high-PGL, low-closeness winners reported a lucky feeling of 3.67, and high-PBL, low-closeness losers reported an unlucky feeling of 3.17. These were the highest ratings of comparison groups made up of the remaining 2x2 median splits of outcome-congruent luck belief and closeness. Recall also, that there was no significant difference between the paths from outcome-congruent luck feeling to either LG or Mins, across the winners' and losers' model. Activation occurs when there is a deviation from expectation, into what might be considered 'positive' territory (i.e., winning) as well as 'negative' territory (i.e., losing).

In summary, when an outcome conforms to prior expectations it evokes neither attention nor explanation. However, when an outcome deviates from prior expectations an *activation* results, monotonically increasing with the deviation of the actual outcome from the prior expectation.

6.3.4 Mechanisms that Translate Activation into Prospective-type Luck Feelings and Risky Choice

How then does an activation become a lucky feeling and lead to risky choice? I return to some of the earliest work in the area of luck for further insight. Wagenaar & Keren (1988) explain conceptions of luck, with their research first being conducted among professional gamblers and then later among non-gamblers. According to Keren & Wagenaar (1985, p. 152), professional gamblers "regard luck as a concept that refers to a person", and most of the subjects they interviewed "... perceived luck as having a wave form." The central feature of luck is for their interviewees is that it affords advantage to those who *detect* the presence of luck, and make gambles accordingly.

Recall also the study by Wagar & Dixon (2006) where professional gamblers were provided two decks of cards from which players drew cards in an attempt to accrue winnings. One deck provided a negative payoff, and the other provided a positive payoff. Before the players could verbalise which of these decks were 'bad', they registered a galvanic skin response, indicating that a non-conscious awareness occurred in advance of a conscious one. Moreover, the players began to choose more frequently from the 'good' deck before they could verbalise awareness of their action. A non-conscious awareness and behaviour can precede a conscious awareness.

The studies demonstrate that the boundary between thinking and feeling is a fuzzy one. This is further highlighted by research in the tradition of the Somatic Markers Hypothesis (Damasio, 1994), the Risk-as-Feelings account (Loewenstein et al., 2001), and the affect-as-information hypothesis (Clore & Huntsinger, 2007). These three approaches to study the interaction of thinking and feeling would cast a luck feeling as one that is affective-cognitive, with a luck feeling reflecting the combined experience of the physiological embodiment of emotions and cognitive deliberation. A luck feeling-as-activation is generally consistent with these views that decision making arises from an interplay of thought and embodied states.

Reliance on an activation to instruct risky choice may be inadvertent and non-conscious or it may be intentional and conscious. Moreover, the mechanisms could well differ by outcome type. For a win-outcome individual, perhaps it is a feeling of confidence that results from activation. Misplaced though it may be, the win-outcome individual may assess a future gamble with a rosy view, a hot-hand fallacy perhaps; an optimistic feeling of some kind. The resulting feeling of having won by a clear margin might be akin to an outcome in a domain of skill. If one were throwing darts at a dart-board, and had recently achieved several bulls-eyes, he or she would surely be more likely to take a gamble for another bulls-eye than if he or she had missed the dart board entirely in those same several shots. A close margin in a game of skill attenuates confidence regarding future performance. Perhaps it is the same for a win-outcome participant in a game of chance: a hyperactive application of a rule in one domain to another domain where it doesn't apply. This is the basis for a number of decision biases: anchoring and insufficient adjustment, confirmation bias, hot hand fallacy, and the gambler's fallacy to name but a few. For losers, perhaps the mechanism is the last of those biases just listed: the gambler's fallacy, or perhaps a loss-aversion. Having just lost, and lost by a large margin, a corrective action to that big loss is to 'double down'. There is no shortage of mechanisms that could mediate the different outcome congruent luck feelings and risk, something that would be of interest for future research in this area. The second formal statement of the theory encapsulates this transfer of activation into risky choice:

> **2) The mechanisms whereby activation transfers to luck feelings and risky choice share a common feature: the application of that activation in a future decision.**

It is important to note here that only prospective-type luck feelings are posited to lead to risky choice. Retrospective-type luck feelings are discussed now.

6.3.5 A Threshold Account for Retrospective-type Luck Feelings

There is a limit to the activation of luck-expectancy feelings of a prospective-type. When a deviation from a prior expectation exceeds a given point, the evoked attention and explanation may result in a re-appraisal of prior expectations. When prior expectations are revised, a reference point shift is likely to occur. The new focus shifts to a counterfactual formulation. That shift may also occur as a result of a counterfactual outcome being personally meaningful[1].

An example bears this out: a leisurely stroll through the park, with an unexpected near-death experience. Now of course, had you thought in advance of the walk that you might be subject to a near-death experience, your plans would exclude that walk in the park. But not knowing in advance, your prior expectation is a pleasant encounter with nature. Imagine though, that as you walk through the grass in the shade of some towering foliage, a large dead branch from a tree crashes to the ground only a meter ahead you. Had you been only a second sooner, this pleasant walk could have been your demise.

This actual experience deviates so far from your prior expectation, that a Bayesian updating of sorts results. The givens in the Bayesian updating are that (a) the branch crashed just in front of you and (b) you paused to secure your shoelaces just seconds before. So with your new reference point in mind (the counterfactual outcome of the large branch mortally striking you), you feel very lucky-fortune to have been spared. In fact, with the givens in mind, it may reasonable to see a broken neck as the *most likely* outcome of any you can think of. Moreover, the closer you are to the impact site of the branch, the more lucky-fortunate you feel. Note here that counterfactual closeness is inversely related to the deviation of the outcome from the expectation. Note also, that having had a shift of reference point, you probably are not experiencing lucky-expectancy feelings, but rather lucky-gratitude feelings.

The combination of the actual and counterfactual outcome are instructive in an adaptive way. The reference shift not only activates lucky-gratitude, it also makes you more keenly aware of the hazards of walking under dead branches. Your next walk in the park could reflect a risk-aversion to walking under dead tree branches, and also an increased vigilance for the presence of dangerous woody masses. This risk-aversion is not the result of activation. Rather, it is the result of a change in the original expectation to reflect the updated awareness of a previously overlooked possibility.

[1]Pritchard & Smith (2004, p. 18) make a strong assertion regarding this: “If an outcome is lucky, then it is an outcome that is significant to the agent concerned.”

Two further theory statements arise from the threshold account for retrospective-type luck feelings:

> **3) A revision of prior expectations occurs beyond a threshold of deviation. Revisions are more likely to occur with significance of possible loss or gain.**
>
> **4) Activation is positively related to both retrospective-type and prospective-type luck feelings.**

In summary, activation is positively related to both retrospective-type and prospective-type luck feelings. However, beyond a given threshold, a reference shift occurs. The prior expectation is no longer the active comparison point for an actual outcome. The new reference point is a counterfactually worse or better outcome.

6.3.6 Rational Explanations Diminish the Activation Potential of the Deviation

When rational explanations exist for systematic or very large deviations from a prior expectation, then the activation from that deviation should be attenuated. Loaded dice and double-faced coins come to mind. Having learned that one has lost (or won) as a result of some deterministic influence, then the deviation is by nature not a deviation. This is another instance of updating prior expectations.

A belief in luck is by nature non-rational. It indicates that deviations from an expectation can *signal* the presence (or absence) of luck. A theory of luck feelings then can accommodate both rational explanations and luck beliefs simultaneously. Ascribing an outcome to chance implies a comfort with lack of mechanism and a reduced need to pursue explanation of chance outcomes. A belief in luck however replaces attributions to chance with attributions to luck. At the same time, more extreme deviations from prior expectations might lead the non-believer to search for an alternative explanation, whilst a believer continues to hold fast that the deviations are a signal of hidden force.

A belief in luck will influence a person not to look for alternative explanations, and at the same time a rational ascription to chance will also influence a person not to look for alternative explanations. This seems at first an inherent contradiction in the theory, but the difference between having a belief in luck and being rational then is the activation that the deviation causes. A rational ascription to chance invokes little or no activation.

A luck belief assumes there is a causal factor in play even though an outcome conforms to those consistent with random chance. A deviation from basic expectations then is a signal for the luck believer to interpret. Recall there is an onus on the luck believer to *detect* when luck is present (Keren & Wagenaar, 1985). Whether the luck belief must be outcome congruent has not been fully tested here. Could a win-outcome be moderated GBL or even PBL in the deviation-activation coupling? It is possible. The inverse may be more likely though: a participant having a far-loss feels strongly unlucky, but has a high belief in personal good luck. So a far-loss might generate an activation that is then interpreted by a high PGL participant that luck will 'even out' in the next gamble, consistent with gambler's fallacy. Perhaps GBL would moderate both outcome and outcome congruent luck feelings, given that GBL is such a strong predictor of both PGL and PBL. Again, these are empirical questions that could be addressed in future research.

The fifth and final theory statement reflects these comments:

> **5) Luck belief will strengthen the deviation-activation coupling when there is no verifiable or otherwise assumed causal factor. The deviation-activation coupling is attenuated with a stronger view that luck is random.**

In summary, activation results from deviation, unless and until that deviation has an explanation. Luck belief reduces the search for an alternative explanation just as rational beliefs increase comfort with a non-deterministic mechanism (i.e., chance).

6.3.7 Summary of the Activation Theory of Luck Feelings

Figure 6.1 provides a graphical representation of the theory, which I have called the Activation Theory of Luck Feelings (ActLF). I first call attention to the normal curve in the middle of the figure, which is an individual's implicit probability distribution of an expected outcome (E_o). The thin tails of the curve obviously represent a lower probability outcome. Moving down in the figure, I call attention to the bolded arrows pointing diagonally down the page. These lines represent deviation from the expected outcome. An outcome could fall anywhere along these arrows. The arrow to the left is a negative outcome, the arrow to the right is a positive outcome. Consider the dice game from Chapter 5: One could win by a couple of rolls (and thus be located closer to E_o) or win by many rolls (and thus be closer to A). Alternatively, one could lose by many rolls (and thus be closer to D). The points labelled 'A' and 'D' correspond to cells in Figure 5.12.

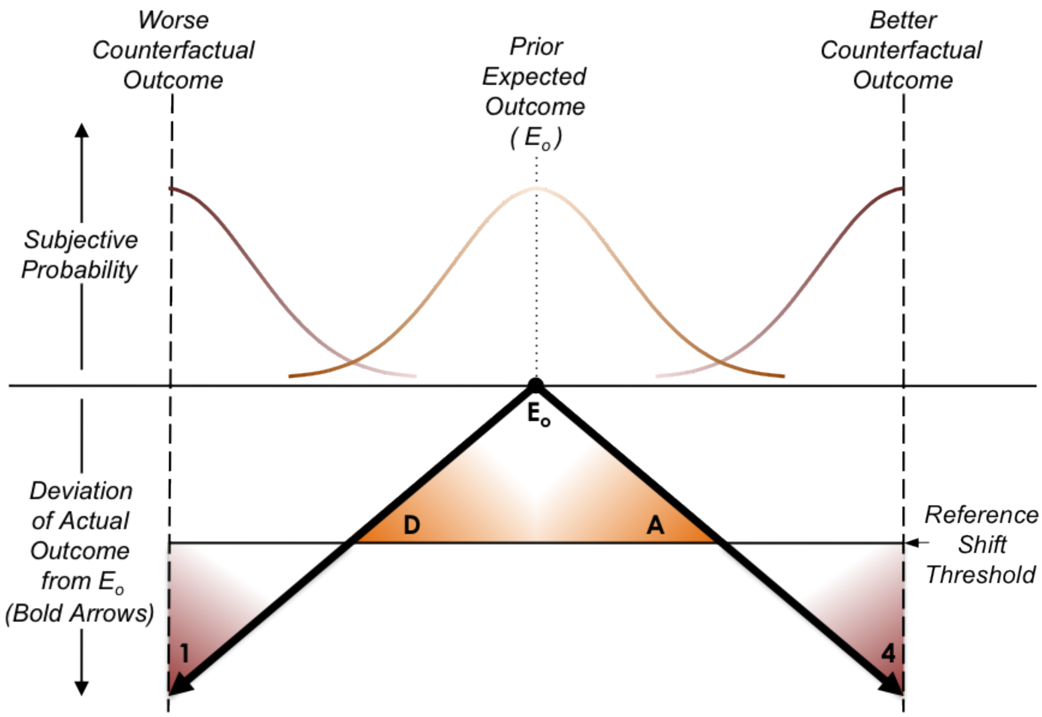

Figure 6.1: A Representation of the Activation Theory of Luck Feelings - The ActLF theory relates an actual outcome (bold arrows) with a prior expectation E_o, and counterfactually imagined better and worse outcomes. Shaded areas correspond to stronger luck feelings. Orange areas (below) and curve (top) = prospective-type luck feelings. Purple areas (below) and curves (top) = retrospective-type luck feelings. Labels A, D, 1 and 4 correspond to the cells in Figure 5.12 on page 262.

The orange-shaded areas in the middle triangle indicate that a person would be experiencing greater activation. Moving further down, the arrow crosses over the horizontal line labelled 'Reference Shift Threshold'. Beyond that line an individual would move from the orange-area (luck-expectancy) and into the purple area (luck-gratitude). In the orange areas, the reference point is E_o. In the purple shaded areas, the reference point is the counterfactual outcome. The labels in these areas correspond also to those in Figure 5.12.

Looking again to the upper portion of the figure, observe the two distributions associated with the counterfactual outcome lines. An individual evaluates the counterfactual outcome as being the one that should have happened, that was more likely (i.e., it was unlikely that you would have stopped to tie your shoe) where the counterfactual outcome seems the most probable to have happened. Does a deviation actually result in a retrospective-type luck feeling? Perhaps the relation between the two is fully mediated by the extent to which a reference shift (and assessment of proximity to a counterfactual outcome) occurs. I posit that a reference shift *results from* an extreme deviation, or a deviation toward an extremely significant counterfactual outcome.

One can see from the figure that counterfactual closeness and deviation from a prior expectation are inversely related. This accords with the results provided in Figure 5.12. The findings from Teigen's program are thus reconciled to those from the study in Chapter 5. Activation explains the origin of both retrospective-type and prospective-type luck feelings. Crossing the threshold for a reference shift would not alter the monotonically increasing relationship of deviation to luck feeling for either type.

The ActLF accomplishes each of the objectives laid out in Section 6.3.2. It integrates retrospective- and prospective-type luck feelings. It accounts for the known antecedents of luck feelings, namely closeness, belief in luck and outcome. It assimilates the two valences of luck feelings, that is lucky and unlucky feelings. And it predicts when and to what extent risky choice will arise from luck feelings. It has also reconciled the various findings—with one notable exception, Wohl & Enzle (2003)–in support of the counterfactual closeness hypothesis.

Most studies in support of the counterfactual closeness hypothesis have not included dependent measures of risky choice. There is however one that did, and it does not at first appear to accord with the ActLF. Recall the findings of Wohl & Enzle (2003): relative to participants who experienced a near big win, those who experienced a near big loss generated more counterfactuals and gambled more. These were interpreted as support for a prediction that the person who nearly loses everything should feel more lucky and gamble more. [That prediction was based on Teigen (1996) and Teigen (1997).] The ActLF would predict that deviations of a similar degree, regardless of the direction (i.e., positive or negative outcomes), should generate a similar degree of activation and therefore luck feelings. Thus, in this instance, the Teigen-based prediction and the ActLF-based prediction are at odds. Two observations may stimulate a reinterpretation of Wohl & Enzle's findings to conform to predictions of the ActLF.

The first observation is that their reported counterfactuals were not substantial, especially in the near big win condition. In the first study they report with a sample size of 30, spontaneously generated counterfactuals were coded as -1 for downward (i.e., near big loss), +1 for upward (i.e., near big win), and 0 for for neither. Based on a sample size of 15 in each condition and an assumption that no one in the near big win condition reported a downward counterfactual, only 2 out of 15 participants reported a counterfactual (mean rating for the condition was 0.13). For those in the near big loss condition, assuming no one reported an upward counterfactual, only 7 out of 15 participants reported a counterfactual (mean rating for the condition was -0.47). Although the difference between the two was reported to be statistically significant (using a t-test), it was not reported whether these were different from zero. Perhaps the near big loss is different from zero, but it is probable that an average of 0.13 with sample size of 15 would not be. The counterfactual closeness hypothesis relies on counterfactuals generating a lucky feeling. From the findings, it appears that only 9 out of 30 participants were thinking counterfactually at the conclusion of the game.

The second observation regards the composition of the winning and losing sections of the wheel. The wheel of fortune was configured with a win result for six of seven sections, and the average of the win sections was 20 tokens[1]. Perhaps the stimulus was perceived by participants in a way different to what Wohl & Enzle proposed. It is possible that participants' prior expectation would have been a win (6 out of 7 chance) of approximately 20 tokens (on average). Only the near big loss approached a deviation of that expectation. The near big win condition for most participants could have been a middle-of-win-territory result that conformed to prior expectations. Even among the near big loss participants, only about half reported a counterfactual. According to the ActLF, these participants would experience lucky-relief after a reference shift and thus there would be not effect on prospective-type luck feelings that would

[1]The average for all possible outcomes on the wheel, including the loss of the initially granted 5 tokens if a participant hit bankrupt, was 16.42 tokens. This is very close to the final outcome all participants experienced, 20 tokens

lead influence risky choice. However, there remain 8 of the 15 participants in that condition who would, from the perspective of the ActLF, be experiencing a prospective type of luck feeling that resulted in an influence on risky choice. In further support of an ActLF interpretation of these results, Wohl & Enzle report that the correlation between counterfactual thought and self-perceived luck was negligible (and not statistically significant), and that counterfactual thought did not mediate gambling behaviour. These findings are consistent with ActLF predictions.

6.3.8 Limitations and Future Research

The ActLF can serve as a foundation for future research and to address limitations of the studies I've reported herein. Future research might begin by comparing different luck feelings measures as outcomes of the same experimental manipulations. The ActLF would predict that luck-gratitude (-relief; -fortunate; -regret) should differ from luck-expectancy in a systematic way. Luck-expectancy is predicted to increase with activation up to a point where a reference shift occurs, while retrospective-type luck feelings remain constant (and low). Past the reference shift point, prospective-type luck, that is luck-expectancy should drop to a low level and remain constant, while retrospective-type feelings increase with deviation, or more accurately as the deviation approaches a counterfactual outcome held in the participants mind. Taking an additional measure of a reference shift would strengthen any findings consistent with this predicted pattern.

A second line of enquiry would compare risky choice measures against measures of both types of luck feelings. These risky choice measures could be further refined to include and exclude the domain (recall the example of walking under trees with dead branches). The ActLF would predict that prospective-type luck feelings are applicable to a larger set of domains, whilst retrospective-type are constrained to the original domain.

Other lines might take a housekeeping approach, to investigate the various types of manipulations that would affect the two different types of luck feelings. It should be noted however, that a large body of work already exists in both domains though. This approach would focused on the integration of different measures of risk and feelings with different manipulations of luck feelings.

Further application of this theory to previous work would also be advisable. Namely, the multitude of findings from Teigen's program have yet to be filtered through the lens of this theory in a systematic and comprehensive manner.

6.4 Thesis Summary

One can drink *Lucky Beer* whilst eating *Lucky Nuts* and reading *Lucky Magazine*. This can be done in *The Lucky Country* at *The Lucky Shag Bar* or sitting on the idyllic shores of *Lucky Bay*. In the background, one might hear Mary Chapin Carpenter singing *I Feel Lucky*, or *The Lucky Wonders* singing about their *lucky stars*. Later, one could ride home on a *Lucky Scooter* and settle in to watch the 2012 movie, *Four Times Lucky*, or the 2011 movie, *Lucky*, or any of the other 840 IMBD (movie database) entries returned for queries of the words "luck" or "lucky" in the title or episode name. With more than 2.5 *billion* combined internet search returns for these same query terms, there is no practical limit to the number of luck-related products, events, courses, establishments, icons, games, characters or locations in which one might take an interest.

There is however, a severe limit to the current empirical understanding of the 'psychology of luck', the effect that luck beliefs and lucky feelings have on decision making. This is surprising given that luck concepts have been part of human thought for millennia and were spontaneously emergent across isolated cultures that predate even the Common Era. Surprising all the more, because the psychology of luck is potentially informed by, and informative to, many significant psychological constructs about which much is presently known: belief, emotion, attitude, causal reasoning, and probability judgement, to name but a few.

Luck is a contrivance of the mind; a conceit to contend with one of the basic elements of the human condition—uncertainty. Indeed, some view luck as a bona fide mechanism that operates deterministically. In this view, good and bad luck reflect the outputs of a causal apparatus, the supernatural workings of which are only conjecturable by observing putative patterns or other indicators. And, because the presence of luck cannot be objectively verified in advance of an outcome, it is by nature a matter of belief. At the moment of decision the presence of luck might be therefore intimated by a *feeling*; a subjective sensing of the force luck will exert over chance, or over the insufficiency of one's own skill or control. At a fundamental level, a 'lucky feeling' provides the luck-believing decision maker with information that might alter calibration of outcome probabilities. Nevertheless, despite ample anecdote and a convincing logic, there is little empirical enquiry of the central question of this thesis: Do lucky feelings influence decisions?

A belief in luck is logically antecedent to lucky feelings. Thus, it was important to first establish a valid and reliable measure of belief in luck, taking into account the possible dimensionality of luck beliefs. Previous conceptualisations of luck beliefs are in disagreement regarding the dimensionality of luck beliefs, and the most recent scale had not previously been subjected to validation outside of the original publication. I aggregated data from five studies to examine the factor structure of existing measures of belief in luck, the most recent of which is a 22-item scale. I refined existing measures to a 16-item Belief in Good Luck Scale (BIGL16), confirming four factors of belief in luck: A General Belief in Luck (GBL); a Belief in Personal Good Luck (PGL); a Belief in Personal Bad Luck (PBL), and a Belief that Luck is Random (LIR). I embedded these luck belief dimensions in structural models containing superstitious beliefs, cultural background, intelligence, and understanding of randomness. Items for each luck belief dimension displayed convergent and discriminant validity, and the models demonstrated nomological validity for the dimensions. Several mediation analyses supported a compelling structural arrangement of the four luck belief dimensions, where LIR is antecedent to GBL, which in turn is antecedent to both PGL and PBL.

Two of the five studies included in the development and validation of the BIGL16 were manipulation studies that are reported in depth in two separate chapters. The first study reported was a *counterfactual priming study* (CFP study), where participants were asked to recall a past event and formulate alternative outcomes to the actual outcome. A theory-based composite measure of lucky feelings was included in this study, as well as measures of positive and negative affect. Ultimate dependent variables were two types of overconfidence in a knowledge task.

Extending the findings from the CFP study, in a second study I used a manipulation of lucky feelings with a real-time outcome: winning or losing in a competitive game with material consequences. Win-outcome participants were allowed to leave the study halfway through the allotted time, whereas loss-outcome participants were required to stay. This *dice game manipulation study* (DGM study), also included unlucky feelings as well as lucky feelings, to address a question regarding the relationship of feeling lucky to feeling unlucky. Single item questions were used for each type of lucky feeling. Ultimate dependent variables were related to risky choice. The first set of questions asked about a gamble closely related to dice game: a hypothetical repetition of the original game and a variant of that game involving a coin toss instead of the throw of a dice. A second set of questions asked about confidence in these 'game gambles', a third set of questions asked about an unrelated lottery-style gamble focusing on amount invested, and a fourth set of questions were related to ambiguity tolerance in a gamble where alternatives differed by knowledge of odds.

The design of these two manipulation studies addressed prominent questions that are integral to the central thesis of the role of lucky feelings in decision making. These questions concern counterfactual thinking as a determinant of lucky feelings, positive and negative affect as alternative explanations, the relation of lucky feelings to unlucky feelings, and different types of risky choice that are potentially influenced by lucky feelings. The role of luck belief dimensions in lucky feelings and risky choice is woven into these questions, where PGL and PBL are tested for both independent and moderating effects.

The most prominent theory in the psychology of luck holds that counterfactual thinking is essential for generating lucky feelings. Counterfactual thinking compares an actual past outcome to an imagined hypothetical better or worse outcome. The theory asserts that counterfactual closeness—how readily imagined an alternative hypothetical outcome is to the actual outcome—should predict lucky feelings. For example, compared to a far-win, having recently experienced a close-win a person should feel a greater sense that the outcome was mutable, and therefore luckier. Of the five studies used to develop and validate the BIGL16, the CFP and DGM studies contained experimental manipulations of lucky feelings with measures of counterfactual closeness for a prior outcome. Across these two studies, I found mixed results that counterfactual closeness explains variance in lucky feelings. In the CFP study counterfactual closeness explained no additional variance in a theory-based composite measure of lucky feelings beyond that explained by mere counterfactual direction.

In the DGM study, counterfactual closeness for loss-outcome participants was associated with higher lucky feelings, and lower *un*lucky feelings. For win-outcome participants, counterfactual closeness was associated with only higher unlucky feelings. The result for loss-outcome participants was in line with the counterfactual closeness hypothesis prediction *for winners*. The absence of result for win-outcome participants in the domain of lucky feelings was null-support for the counterfactual closeness hypothesis, while the result for win-outcome participants in the domain of unlucky feelings was in line with the counterfactual closeness hypothesis prediction *for losers*. The combined counterfactual closeness results of the CFP and DGM studies stimulate a reconsideration of the counterfactual closeness hypothesis.

The importance of valid and reliable measures of luck belief dimensions is borne out in further findings from the CFP study. In addition to the direct effect of counterfactual closeness on lucky feelings, there was a direct effect of belief in personal good luck (PGL). In the DGM study, PGL had a direct positive effect on lucky feelings and PBL had a direct positive effect on unlucky feelings for both win- and loss-outcome participants. That is, a higher belief for both PGL and PBL was associated with both greater lucky and unlucky feelings respectively. Moreover, PGL moderated the effect of closeness on lucky feelings, such that closeness was associated with greater lucky feelings for believers experiencing a loss outcome. This result is perhaps illustrative of a resilience effect, for luck believers facing a recent negative outcome.

There are many theories of the role of positive and negative affect in decision making. The *somatic markers hypothesis*, the *affect-as-information hypothesis*, and the so-called *affect heuristic* all generally assert that perceptual processes relay information to a cognitive appraisal via physiological states that are more or less consciously interpretable. How one *feels* about a prospect is a function of both core psychophysical processes and effortful deliberation. States of being that arise from the interplay of these two systems can be described as affective-cognitive, a category to which lucky feelings most certainly belong. This begs the question of whether lucky feelings are equivalent to affect, or so wholly subsumed by affect that the effects of lucky feelings and affect on decision making are indistinguishable. To wit, it is possible that a prior outcome alters positive or negative affect, which in turn leads to variance in risky choice, and lucky feelings are merely epiphenomenal.

Previous research on lucky feelings indicates that affect and lucky feelings are distinct. However, measures of affect have been limited to a single survey item asking about happiness (and in one instance a second item about sadness), in contravention of recommendations by respected affect researchers. In the counterfactual priming (CFP) study, I used an established measure of positive and negative affect and the aforementioned theory-based composite measure of lucky feelings, eliciting participant ratings on these measures both prior to, and after the manipulation. Using change scores, I found that the effect of the manipulation on lucky feelings was mediated by both positive and negative affect. The change in both positive and negative affect predicted about 16% of the variance in the change in lucky feelings. Change in positive affect was correlated 0.389 with change in lucky feelings, whereas change in negative affect was correlated -0.233 ($ps < .001$).

The CFP study also tested the differential impact of affect and lucky feelings on two different types of overconfidence. The lucky feelings composite had a direct positive effect on overconfidence regarding objective performance in a knowledge task, *overestimation*. The lucky feelings composite and PGL interacted to predict overestimation, such that higher lucky feelings and higher PGL were associated with higher overestimation. However, neither positive nor negative affect had a direct effect on overestimation. For a measure of overconfidence regarding performance relative to a peer, *overplacement*, there were no direct effects. However, positive affect interacted with PGL such that higher positive affect and higher PGL was associated with greater overplacement. These results are interpreted as a weak form of double dissociation of affect and lucky feelings and two types of overconfidence, and argue that although affect may mediate the impact of a prior experience on lucky feelings, affect and lucky feelings are differentiable in terms of effects on dependent variables. The importance of luck belief is underscored in these results with PGL moderating the effect of lucky feelings and affect on overestimation and overplacement respectively.

In the dice game manipulation (DGM) study both lucky and unlucky feelings were modelled as mediators of the game outcome on hypothetical decisions involving risk. Two separate models were used to explore the differences between loss- and win-outcome participants in terms of the system of variables that included personal luck beliefs (PGL and PBL), lucky and unlucky feelings, and risky choice. Lucky and unlucky feelings were found to be non-unitary in terms of both covariance with one another, and also differences in the active predictors of each across the loss- and win-outcome models. The difference in the coupling of lucky and unlucky feelings across loss- and win-outcome participants was quite large; lucky-unlucky feelings were correlated -0.338 ($p < .001$) and -0.195 ($p < .05$) respectively, even though the difference in correlations was not found to be significant ($p = .15$).

As mentioned above, for loss-outcome participants, PGL, counterfactual closeness, and the interactive effect of the two predicted lucky feelings. Unlucky feelings were predicted by PBL, counterfactual closeness, *and* PGL. Unlucky feelings in turn positively predicted game-related and lottery-style risky choices. Only lucky feelings predicted gamble-confidence, and did so positively. Ambiguity tolerance was not related to either lucky feelings or unlucky feelings. The total variance explained in these three dependent variables was small, ranging from 3% to 5%, with β's ranging from 0.17 to 0.21 ($ps < .01$).

Also mentioned above, for win-outcome participants, PGL predicted lucky feelings, positively. The interaction of closeness and PGL also predicted lucky feelings, where higher PGL winners who experienced a far-win felt more lucky. Unlucky feelings were positively predicted by closeness and PBL. For win-outcome participants all four sets of risky choice variables were predicted by either lucky or unlucky feelings. Unlucky feelings predicted gamble confidence, in contrast to the loss-outcome model which showed lucky feelings to positively predict gamble confidence. Also in contrast to the loss-outcome model, lucky feelings (not unlucky feelings) positively predicted risky choices. Ambiguity tolerance was predicted with the greatest effect: 12% of variance explained with a β of 0.35 ($p < .01$). The game-related gamble and the lottery-style gamble were predicted by lucky feelings with 4% and 7% of variance explained, respectively, and β's of 0.19 to 0.27 ($ps < .01$), respectively.

The influence of lucky and unlucky feelings on risky choices was congruent with participant outcomes. For loss-outcome participants, unlucky feelings influenced risky choice, whereas for win-outcome feelings, lucky feelings influenced risky choice. That gamble confidence is predicted by the non-congruent feelings is a surprising finding, and unexplainable. Of all dependent variables for both loss- and win-outcome participants, winners' ambiguity tolerance was the most responsive. Perhaps the archetypal lucky feeling effect on decision making is less related to the quantum of risk than it is to the quantum of uncertainty.

Taken together, the results support several conclusions. The 16-item scale is a valid and reliable measure of luck beliefs, and there is a compelling structural arrangement of luck belief dimensions, which may be valuable for future theory building. The two personal luck beliefs (PGL and PBL) are the important predictors among the four dimensions of luck beliefs. They act as both independent predictors, and PGL moderates prior outcomes and lucky feelings, as well as lucky feelings and overconfidence. The counterfactual closeness hypothesis is unsupported in its previous conceptualisation. Affect and lucky feelings are not unitary, as evidenced by a weak form of double dissociation of affect and lucky feelings from overestimation and overplacement. Lucky feelings and unlucky feelings are also not unitary. The effects of lucky feelings and unlucky feelings on risky choice differ by the nature of a prior outcome. For negative outcomes, unlucky feelings are likely to influence risky choices. For positive outcomes, lucky feelings are likely to influence risky choices. The type of risky choice most affected by lucky feelings (for positive experiences) is ambiguity tolerance in the probability distributions of prospective outcomes. In summary, lucky feelings do influence decisions, though the way in which lucky feelings operate is contingent on the context, the prior outcome, and beliefs in luck.

A new theory is proposed, which explains the previous findings that support the counterfactual closeness hypothesis and well as the present findings. The Activation Theory of Luck Feelings (ActLF) describes retrospective-type and prospective-type luck feelings as having the same determinant: activation directly proportional to the deviation of an outcome from prior expectations. The ActLF explains the present findings in context of prior literature and support for the counterfactual closeness hypothesis. Although predictions from the ActLF have yet to be tested in an *a priori* fashion, the theory holds promise to integrate retrospective-type and prospective-type luck feelings and reconcile different findings regarding counterfactual closeness. The ActLF accounts for the known antecedents of luck feelings, assimilates the two 'valences' of luck, and most importantly predicts when, and to what extent, risky choice will arise from luck feelings.

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Appendix

Partial Least Squares Modelling

Introduction

I include this appendix to assist the reader who may be unfamiliar with Partial Least Squares Modelling (PLS). It is not intended as a manual for conducting PLS analyses, but rather as a guide to assessment and interpretation of results from PLS analyses. It assumes only an understanding of regression.

A General Introduction to PLS

My personal experience with PLS dates to November 2007 when I attended a three-day workshop delivered to faculty and students of the University of New South Wales by Wynne Chin who authored PLS-Graph, one of the early versions of software to implement PLS.

At about that same time, I was finishing data collection for a pilot study related to this thesis. I had found that moderated relationships were probably a part of the theory that linked together beliefs in luck, lucky feelings, and risky choice. I had also developed a view that a theory of belief in luck, lucky feelings, and risky choice would probably involve more than just a single construct to link the belief in luck and risky choice, a sort of multiple simultaneous mediation, if you will.

Of course, I could use traditional ANOVA or regression techniques to analyse my data. I in fact did at that time, and do presently in the work before you where I report both ANOVA and regression throughout the empirical chapters. However, in comparison to a modelling approach such as PLS, these traditional techniques seemed to lack a coherence and holism and have a few other limitations I will discuss below. So it was that I began to incorporate PLS into my thinking regarding the design of studies, and eventually the technique found a prominent place in my work, recently resulting in peer-reviewed publication (Bohle, Willaby, Quinlan & McNamara, 2011).

It is my view, and indeed my practice, that investigating data arising from a theory-building exercise should begin with simple, straightforward and focused analyses and proceed to a more advanced one that can represent the system of measured variables as a whole. The former is often accomplished best with simple, straightforward and focused metrics such as select counts, means and correlations—and associated inferential statistics that may be possible. Sensitive to the individual variables and smaller clusters of variables, the system as a whole can be brought into focus using a modelling technique such as PLS[1]. Like a puzzle, the image that presents when all the pieces are in place can be simultaneously surprising and gratifying.

Origins and Current Use of PLS

Partial Least Squares Modelling (PLS), sometimes called Partial Least Squares Structural Modelling or Partial Least Squares Path Modelling was originally developed by Herman Wold (Wold, 1985; Wold & Lyttkens, 1969). It is considered a "second-generation regression technique" (Gefen, Straub & Boudreau, 2000) because it has the capacity to simultaneously model relationships among many independent and dependent variables.

The earliest implementations of PLS required considerable knowledge of basic programming languages, mathematics, and statistics. However, many user-friendly software packages have now been developed specifically to implement PLS. Some examples of programs that I've used are PLS-Graph (Chin & Frye, 2003), WarpPLS (Kock, 2010), and SmartPLS (Ringle et al., 2005). Other popular software packages that implement

[1]A model can represent a theory, or at least a model can assist in theory development through the specification of the relations among the various constructs inherent to a theory. In the words of Frigg & Hartmann (2009, n.p.), "The separation between models and theory is a very hazy one and in the jargon of many scientists it is often difficult, if not impossible, to draw a line... A look at how models are constructed in actual science shows that they are neither derived entirely from data nor from theory... Model building is an art and not a mechanical procedure."

For me, the objective of building a model that links belief in luck through lucky feelings to risky choice is tantamount to building a theory. The exercise is admittedly exploratory given the paucity of theories on lucky feelings. All the more reason to employ PLS; "... because of its prediction orientation, PLS SEM is the preferred method when the research objective is theory development..." (Hair, Ringle & Sarstedt, 2011, p. 143).

PLS, but do not have PLS as their sole function, are SPSS (in the Python Extension Module), R (the PLSR package), SAS, and MATLAB.

Although PLS is largely unknown to most psychology researchers[1], it has recently seen widespread adoption in other areas of social science, namely information systems, marketing, and to a lesser extent strategic management (Albers, 2010; Henseler et al., 2009; Hulland, 1999). As evidence of this recent widespread adoption, from 2005 to 2008, nearly 20% of articles published in two prominent journals in information systems used PLS[2] (Urbach & Ahlemann, 2010).

These fields where PLS has found considerable penetration share several characteristics with psychology relating to a common foundation in social science. For example, the technology acceptance model (Davis, 1989, TAM) has been repeatedly studied using PLS, as has the revised version of that model, the unified theory of acceptance and use of technology (Venkatesh, Morris, Davis & Davis, 2003, UTAUT; for the model see page 447, also reproduced below)[3]. I provide the UTUAT model in Figure **??** to demonstrate the similarities between the constructs used in it, and those that might be used in psychology.

The UTAUT was developed in part from the Theory of Reasoned Action (Ajzen & Fishbein, 1980), developed by two highly respected scholars of psychology. It is often used to predict the adoption or use of new technology systems, for example desktop computer applications, in organisations (Algahtani, Hubona & Wang, 2007). Reading the model from left to right, note that predictor constructs deal with expectancies, the influence of other people, and some environmental or situational factors that are thought to influence the behaviour of interest. To the bottom of the model are located a number of moderators. There is a single mediator of behavioural intention for all but

[1]A database search of Proquest Social Science Journals for peer-reviewed articles that included the terms 'psychology' and 'partial least squares' anywhere in the text of the document returned 47 entries in 29 journals. Of these journals only five appeared to have general or applied psychology as their focus (i.e. *Journal of Applied Psychology* and *Journal of Social Psychology*; but not *Dementia and Geriatric Disorders* or *Experimental Brain Research*). Restricting the search to general or applied psychology journals reduced the article count to nine.

[2]As an example of the popularity of PLS, SmartPLS had an installed user base of over 25,000 registered users at mid-year 2011 (Ringle, Wende & Will, 2011).

[3]A google scholar search for articles citing the original TAM article that included the exact string of "Partial Least Squares", returned 996 entries. A search for articles citing the UTAUT article that included the exact string of "Partial Least Squares", returned 616 entries.

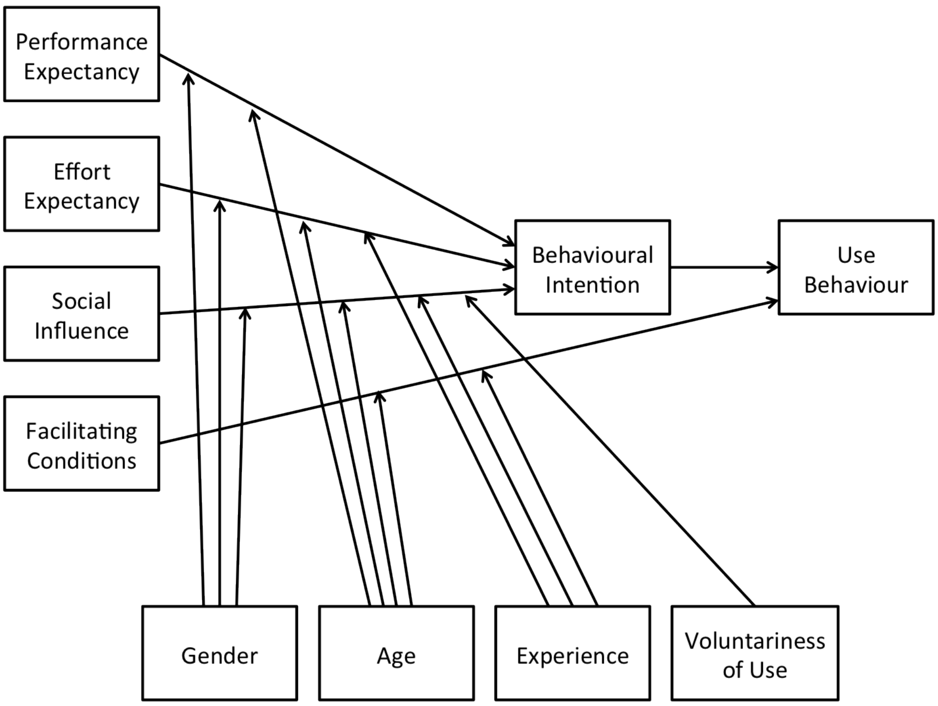

Figure 2: An Information Systems Model Built on Psychology Foundations - This model has been repeatedly tested using PLS.

one of the predictor constructs of the final dependent variable, Use Behaviour.

Because they are both modelling techniques, Partial Least Squares is often compared to Covariance-Based Structural Equation Modelling (CB-SEM). There are a number of published articles comparing the two techniques with the conclusion that PLS and CB-SEM are not substitutes or replacements for one another, but rather they should be seen as complementary techniques attuned to different research objectives and dataset characteristics[1].

Many researchers who have not heard of PLS are aware of CB-SEM and the software packages used to implement it (LISREL, EQS, AMOS, and a number of others), and are familiar with some basic concepts and considerations of CB-SEM, including how to assess and interpret CB-SEM results. Although PLS and CB-SEM share some important features, they are quite different in some very important respects. I will touch on these below, but for now I urge the reader to set aside any understanding of CB-SEM as a source of insight into PLS. A better starting place to understand PLS is multivariate regression.

Basic PLS Output: An Example

Perhaps the most basic and important point for someone unfamiliar with PLS is that the commonly used numerical outputs of PLS are equivalent in meaning and interpretation to the most commonly used outputs from a regression analysis. These are t-statistics, β values, and R^2 values.

The t-statistic corresponds to a p-value for a given sample size. The β value is the standardised regression coefficient between a dependent and independent variable. The R^2 value, also known as the coefficient of determination, is the proportion of variance in a dependent variable accounted for by an independent variable (or multiple independent variables — more on this in a moment.).

To be sure, there is more extensive output generated from a PLS analysis than just t-statistics, β values, and R^2 values. But it is important to keep in mind that at a very

[1] See (Reinartz, Haenlein & Henseler, 2009) for a Monte Carlo simulation study that directly compares the two techniques given various data properties, and see Table 2 of Hair et al. (2011, p. 144) for summarised guidelines to adjudicate the choice of PLS or CB-SEM taking into account research objectives and dataset characteristics.

basic level, PLS is estimating regression coefficients using ordinary least squares[1], just the same as linear regressions conducted in say, SPSS or SAS.

In Figures 3 and 4, I present examples of a measurement model and a structural model. These are taken from Chapter 3. In that chapter, I discuss the specification[2], assessment[3], and interpretation[4] of the 16-item Belief in Good Luck Scale (BIGL16). As can be seen comparing the two figures, the elements that comprise the models are constant across the measurement model and the structural model. The only difference between the measurement and structural model is the output (numbers) and objectives of assessment. I will discuss the differences in objective assessment on page 330. For now, I focus on the elements that comprise a model, and the different outputs.

There are three main elements in a model. The first is the indicators, represented by yellow rectangles in Figure 3 and 4. The second element is the latent constructs, indicated by blue circles.

Note that each latent construct has at least a single indicator, and can have many. Note also that all arrows in the figure point from a construct to an indicator[5]. A 'score' for each case in a dataset is calculated for each latent construct using a weighted combination of the constructs' indicators, and is analogous to a factor score.

The paths between the constructs are the third element in the model. In theory development, each path can be seen, or function as, a hypothesis. The direction of the relationship, that one construct has an arrow pointing to another construct, can

[1]The name Partial Least Squares, takes its name in part from ordinary 'least squares' regression estimation. The 'Partial' of Partial Least Squares refers to the sequential estimation conducted through the model. It is a 'partial' information technique, as compared to CB-SEM, which is a whole information technique. I will discuss this a little more in a later section that touches on the underlying algorithm of PLS.

[2]By specification I mean, the specifying of the composition of the model; the rationale of what is included in and excluded from the model, and which paths are of interest and present or absent.

[3]By assessment, I mean assessment of the quality of both the measurement model and structural model, both of which I describe momentarily.

[4]By interpretation, I mean the explanation of the final model relative to the original theory and specification. A few questions that might be asked in the interpretation are: What was expected, and what was found?; If there are small or large differences in the proposed and final model, to what can they be attributed?; What implications are there, given the final model, for theory building?; In general, What does the model *say*? What does it *not say*?

[5]This is the case for a reflective construct. There is an alternative, called a formative construct, where the arrows point from the indicators to the construct. I will not discuss formative constructs, as there are none in the models throughout my thesis.

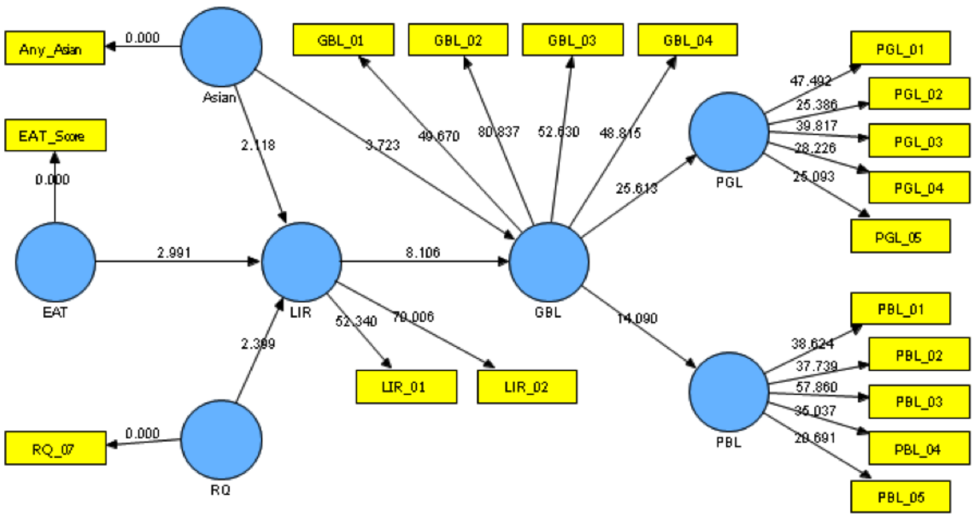

Figure 3: Example: PLS Measurement Model - Bootstrap t-values (500 resamples) are reported for each path and indicator loading.

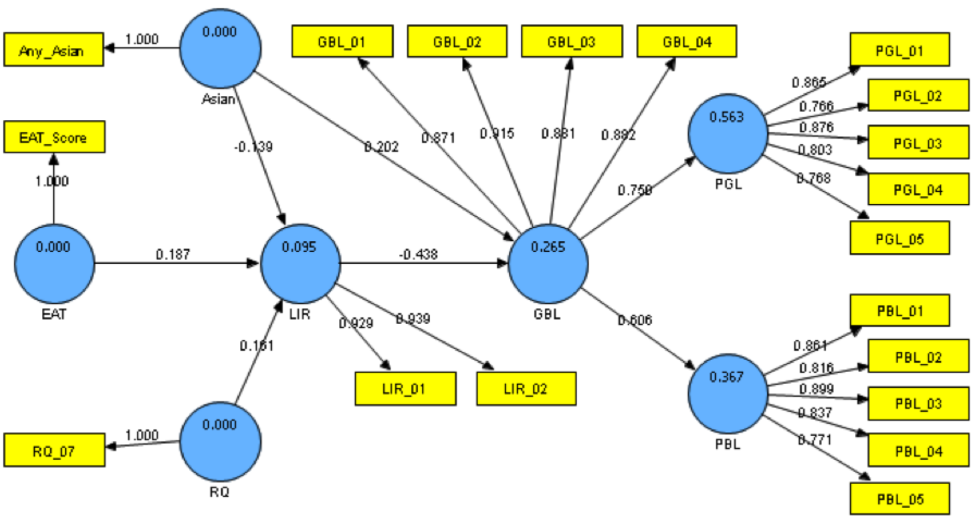

Figure 4: Example: PLS Structural Model - Indicator loadings, path coefficients (β values), and R^2 values for the proposed model.

indicate causality, or merely correlation. Whether one asserts causality or correlation should be made clear during model specification.

In the measurement model in Figure 3, there are numbers associated with each arrow in the model, whether it be a path between constructs, or the link from a construct to an indicator. For the paths between constructs, the number is the t-value of the path coefficient. For the arrows that link a construct with it's indicators, the number is the t-value of the 'outer loading'. The outer loading is analogous to a factor loading, the correlation of an item with the latent variable score.

In the structural model in Figure 4, there are a different set of numbers associated with each arrow, plus there is a number inside the blue circles. For the paths between constructs, the number is the standardised path coefficient, essentially a standardised regression coefficient. For the arrows that link a construct with it's indicators, the number is the outer loading.

The number inside the blue circles is the coefficient of determination, or the R^2. This number provides an indication of the extent to which the predictors of a given construct explain the variance in that given construct. Note that constructs which do not have an arrow pointing to them have an R^2 of '0.000'. This is because there is no variance explained in those constructs without predictors. Note also that for single indicator constructs, the t-value (in the measurement model) of the outer loading is '0.000' and the loading (in the structural model) is '1.000'. For these single indicators, the loading is 1.000 because the indicator and the latent construct score are perfectly correlated, the latent construct score is equal to the single indicator.

These values presented in the measurement model and structural model can be read directly from the graphical presentation as in Figures 3 and 4 or can be output to a table upon request of the user. In addition to the t-statistics, β values and R^2 values, there is a substantial amount of additional output in tabular form, some of which I discuss below.

Features of PLS

There are several features of PLS that influenced my decision to use it in the analyses herein. I first list these, then discuss each one in turn. Where relevant and practical, I describe the underlying mechanics that give rise to a particular feature.

- Latent variables are used in the models, that retain each of the individual items to form a single construct.
- The relationships among many independent and dependent variables can be tested simultaneously.
- There are few restrictions on the type of data or construct that can be used.
- PLS tolerates model complexity very well. Models can contain dozens of constructs and hundreds of items.
- Sample size requirements for PLS are similar to those for multiple regression.
- Statistical significance testing in PLS is non-parametric.
- Model quality criteria include much more than just statistical significance testing or fit indices, extending to convergent, divergent, and nomological validity.
- Compared to CB-SEM, PLS is better suited to exploratory, theory-building endeavours.
- PLS is an excellent tool for testing multiple mediation and moderation, including three-way interactions.
- SmartPLS, the software I use to implement PLS, has an intuitive graphical user-interface with extensive, yet neatly-organised output. The program is very stable and there is a large and helpful user community.

Latent constructs are used in the models, that retain individual items.

In PLS, individual items can be retained and combined into a single latent construct. Where the target of measurement is not subject to direct observation (e.g. a belief or attitude), the construct is considered 'latent'. Of course, psychology, is replete with latent constructs. Retaining the multiple items in a scale has the advantage of retaining the original variance from the items that make up a scale, thus improving both prediction accuracy as well as providing insight into the relative performance of individual items in a particular scale.

The combination of individual items is analogous to a factor score (in the case of reflective constructs) where the number of factors is constrained to one. Refer back to

Figure 3 to see an example of some constructs that have single indicators (e.g. EAT) and some that have multiple indicators (e.g. PGL).

Certainly one could calculate a factor score for a given set of items across each case in dataset, and then use that factor score as a regressor or regressand in a regression analysis. The advantage of PLS however, is that this procedure is automatic and effortless, and the contribution of each individual item to a latent construct is tested for statistical significance. Furthermore, each item is automatically tested for a relationship with other constructs in the model, a possibility which is almost always considered undesirable but often left untested in the practice of traditional regression (or at most is investigated through a large correlation matrix of all items with all other items—but not constructs).

The relationships among many independent and dependent variables can be tested simultaneously.

In PLS, although one may retain the terms, one discounts the traditional notion of dependent and independent variables (constructs). Instead, constructs are better thought of as endogenous and exogenous. Exogenous constructs are those that are not predicted inside the model. These are, in a sense, the given assumptions that tie the model to the outside world. For example, one might use sex (male or female), age, and parents' educational attainment as exogenous constructs in a model. Endogenous constructs on the other hand, are those that are predicted by some other construct or constructs within the model. An endogenous construct can be predicted by one or more other constructs, or by one or more interaction terms.

Note the model in Figure 3, there are a total of 19 indicators for seven different constructs with seven different construct-to-construct paths. The construct GBL is predicted by both LIR and Asian, essentially a regression with multiple 'independent' variables.

But what is responsible for the variance explained in GBL? In actuality, all constructs to the left of it: Asian, EAT, RQ, and LIR, where LIR serves as the sole mediator for the three constructs to the left of it. And what is GBL explaining? Both PGL and PBL can be simultaneously predicted by GBL.

In isolation, each of these construct-to-construct paths could be tested using classical regression. But there also are other paths which contain as many as four constructs.

The list below shows all of the paths contained in the model. In some instances there is more than a single path from one given construct to another. For example, look at the different paths from Asian to PGL. There are two: Asian→LIR→GBL→PGL and Asian→GBL→PGL.

Two Construct Paths	**Three Construct Paths**	**Four Construct Paths**
Asian→GBL	Asian→GBL→PGL	Asian→LIR→GBL→PGL
Asian→LIR	Asian→GBL→PBL	Asian→LIR→GBL→PBL
EAT→LIR	Asian→LIR→GBL	EAT→LIR→GBL→PGL
RQ→LIR	EAT→LIR→GBL	EAT→LIR→GBL→PBL
LIR→GBL	RQ→LIR→GBL	RQ→LIR→GBL→PGL
GBL→PGL		RQ→LIR→GBL→PBL
GBL→PBL		

Using a PLS approach, all of these paths are tested simultaneously, and the influence of any one variable in the model can be propagated throughout. Like individual paths, a t-value and β value are calculated for each of the paths above, so if any one path is of theoretical interest, it can be investigated in isolation. If a number of paths are of theoretical interest in some combinatorial manner, they can all be tested together. Thus the reference to a "second-generation regression technique" above. . . that one can investigate on two levels: bivariate/multivariate, and also multiple simultaneous bivariate/multivariate.

There are few restrictions on the type of data or construct that can be used.

Many kinds of data can be used, even within the same construct and throughout the model: categorical, ratio, and interval. Furthermore, any one construct can have items from scales with different anchor points, for example, a construct can be made up of a dichotomous item, a three-point item and a 9-point item.

The PLS algorithm standardises the variables for calculation, so all indicators are effectively z-scores, as are all construct scores. Output can be obtained in standardised or in unstandarised format.

PLS tolerates model complexity very well.

Models can contain dozens of constructs with hundreds of items, without any implications for successful parameter estimation. A more practical limitation on the size of the model is the user: research interests and data collection constraints combine to limit the available data. However, a more important limitation is *philosophical*: parsimony.

The purpose of modelling is (usually) not to create an exact representation of every possible source of variance in the world. The objective of modelling is usually to reduce the complexity of the world, while still explaining a large amount of variance.

Apart from the questionable parsimony of a model that contains 100 constructs, one must also consider the practical issues of communication. How does one summarise such a large model, or discuss each element of it in a journal with maximum page counts for submissions?

Unlike CB-SEM which generates a solution for all parameter estimates simultaneously, the PLS algorithm is iterative. Parameter estimates for different parts of the model are generated sequentially until the stop-criterion is reached.

The stop criterion in SmartPLS is that all parameter estimates in the model are updated to less than 0.00001 from the previous round of estimation. Usually this stop criterion is reached by the fifth or sixth iteration.

Sample size requirements for PLS are similar to those for multiple regression.

Because the PLS algorithm is sequential and iterative, the sample size requirements are based on the portion of the model with the largest predictors. One only has to look for the endogenous construct with the greatest number of paths pointing to it, and consider then what sample size would be required if the model contained only that endogenous construct and it's predictors.

Statistical significance testing in PLS is non-parametric.

This is an important point that merits an extended discussion. How does PLS conduct statistical significance testing? How does that differ from regression?

In linear regression, a p-value for a given parameter (i.e. β) is generated from a t-statistic. That t-statistic is calculated using the simple equation, $t = \frac{B}{SE_B}$, where B is the unstandardised regression coefficient and SE_B is the standard error of that coefficient. This is exactly the same in PLS. In linear regression $SE_B = \frac{s}{\sqrt{n}}$, where s is the sample standard deviation and n is the sample size. This also is exactly the

df	$p = .050$	$p = .010$	$p = .001$
76	1.992	2.642	3.423
87	1.988	2.634	3.406
88	1.987	2.633	3.405
176	1.974	2.604	3.347
199	1.972	2.601	3.340
224	1.971	2.598	3.334
234	1.970	2.597	3.333
424	1.966	2.587	3.314
499*	1.965	2.586	3.310
∞	1.960	2.576	3.291

Table 1: Select t-values and corresponding p-values - A comparison of t-values and p-values for various degrees of freedom. All t-values are generated from the "=TINV(probability,df)" function in Microsoft Excel 2008, version 12.2.7. Degrees of freedom correspond to n-1 for all samples sizes used analyses reported in this thesis. *The bootstrap resample count is 500.

same in PLS. Table 1 presents t-values from Student's t Distribution, for select degrees of freedom and p-values.

The critical difference between regression and PLS is in the way the sample standard deviation and sample size are produced. In linear regression, the dataset from which the sample standard deviation and sample size are taken is the raw data. So, say there are 100 cases in a dataset. The standard deviation would be calculated over that sample of 100, and the sample size would be 100.

In PLS, there is an additional step to producing a standard error, called bootstrapping. With bootstrapping[1], the original sample serves as the source of many resamples. A resample has the same number of observations as the original dataset, in our case 100. A resample is generated via random selection (with replacement[2]) of individual

[1]See Efron & Tibshirani (1993) for explication of the bootstrapping procedure in general. See Chin (1998) for a focused discussion of bootstrapping in PLS.

[2]For individuals unfamiliar with bootstrapping, the choice of random selection with replacement is sometimes viewed with suspicion because it may incorrectly be seen to "overestimate the variability that would be expected" (Williams, 2011, p. 1). The original specification of bootstrapping in Efron & Tibshirani (1993) makes clear the importance of having bootstrap resamples for which n is equal to the original sample, and provide a well-grounded theoretical case for sampling *with replacement*. The aforementioned reference (Williams, 2011) contains an empirical demonstration of the importance of resample n being

Bivariate Pair	SPSS β	SPSS t-Statistic	SPSS p-value	PLS β	PLS t-Statistic	PLS p-value
Y : X1	0.008	0.102	0.919	0.008	0.159	0.874
Y : X2	0.062	0.825	0.410	0.062	1.048	0.256
Y : X3	0.168	2.252	0.026	0.168	2.282	0.024
Y : X4	0.691	12.655	0.000	0.691	14.144	0.000

Table 2: SPSS and PLS Output Compared - A comparison of β values, t-Statistics, and p-values for four bivariate pairs, across SPSS and PLS. The data are taken from the Dice Game Manipulation study, described in Chapter 5. The sample size was 177.

observations from the original sample. I use 500 resamples throughout the analyses presented herein, because this produces stable (e.g. reproducible) t-values (Chin, 1998). A given parameter—say, a β value—is then estimated for each of the 500 resamples. Thus, it is possible to calculate a mean parameter estimate over the 500 resamples, as well as a standard deviation across those 500 resamples. The standard deviation is equated to a standard error, given the target of the resamples is the parameter estimate itself. In other words, the sample size is assumed to be one. It is this standard error, equivalent to the standard deviation, that is then used in the t-statistic equation.

As a comparison across PLS and linear regression, I compared four bivariate coefficients and their t-statistics across PLS and SPSS from a dataset reported in this thesis. These results are presented in Table 2.

The parameter estimates of β values did not differ at all, although the t-statistic did and the resulting p-values were somewhat different, with PLS usually reporting a

equal to that of the original sample. The misunderstanding may originate with a misconception of the purpose of the bootstrapping procedure, and the relation between the bootstrap samples and the estimate of the standard error.

To clarify, the original sample is to the bootstrap sample as the population is to the original sample. When the bootstrap sample is smaller than the original sample, the dispersion of the parameter estimates for resamples will contract relative to the original sample, and thus the standard deviation of the resamples will contract artificially. Note that when a resample contains the same n as the original sample, and is created without replacement that the resample will exactly replicate the original sample.

For the reader who remains skeptical, I provide Table 2 which compares the t-values generated for the same dataset across SmartPLS and SPSS. An extensive literature on the topic of bootstrapping exists. I refer the reader to the original specification and self-directed enquiry to other sources in the event that discomfit persists regarding the resampling procedure.

slightly less conservative value relative to Type I error. Because of the random selection during the bootstrapping procedure, the t-statistics will vary from run to run. This is not a problem when higher number of resamples and good judgement are used.

As regards good judgement, I quote to Jacob Cohen's (1990, p. 1311) conclusions in his article titled, "Things I Have Learned (So Far)":

> The implications of the things I have learned (so far) are not consonant with much of what I see about me as standard statistical practice. The prevailing yes-no decision at the magic .05 level from a single research is a far cry from the use of informed judgment. Science simply doesn't work that way. A successful piece of research doesn't conclusively settle an issue, it just makes some theoretical proposition to some degree more likely. How much more likely this single research makes the proposition depends on many things, but not on whether p is equal to or greater than .05: .05 is not a cliff but a convenient reference point along the possibility-probability continuum. There is no ontological basis for dichotomous decision making in psychological inquiry.

In light of Cohen's comments, the variance of the t-values from run to run in PLS, and between PLS and SPSS is a minor point upon which to stake conclusions. Rather, the rationale behind the experiment in the first place takes greater prominence, as does the coherence of the model as a whole and replication of results.

As regards the number of resamples, I use 500 resamples, in line with recommendations by Chin (1998) and broader convention of the PLS community. If repeated runs for statistical significance testing demonstrate a path to only sometimes meet the $p < 0.05$ level, then I clearly state this is the case. The ultimate focus when using PLS is toward the model as a whole, how the constructs and paths *together* present a coherent representation of the data and the implications for theory. Individual paths are examined toward this end, so it is important to be cautiously conservative at each step, given the final objective.

Regardless, statistical significance is but the first step of many in model assessment. Unlike linear regression, a number of steps follow statistical significance testing before parameter estimates are generated. This is the next point I discuss.

Model quality criteria include much more than just statistical significance testing or fit indices, extending to convergent, divergent, and nomological validity.

In fact, there are two basic categories of assessment in PLS. These are neatly laid out in Henseler et al. (2009)[1]. The first is measurement model assessment and the second is structural model assessment. Measurement model assessment addresses the question: Is the measurement of indicators and latent constructs in the model of sufficient quality to produce accurate parameter estimates? Structural model assessment then addresses the questions: Does my theoretical model fit the data? How good is my proposed representation of the relationships among the constructs, given the data? Is there another configuration that is better?

Until a model has passed measurement model assessment, there is no license to look at the structural model. It requires some discipline by the user to go through the measurement model assessment before looking at the structural model. The steps of measurement are well described by Urbach & Ahlemann (2010, pp. 18-19). Figure 5 reproduces the original Table 4 from page 19, providing a basic checklist.

Mirroring the steps in Figure 5, Chapter 3 provides a guided explanation (and implementation) of the steps of measurement model assessment on page 87, along with more extensive references.

Having verified that the measurement model is adequate, Structural Model Assessment begins. This process has few numerical standards, and is more artful, compared to the measurement model assessment which has many objective standards that are well-known.

Recall our questions addressed in structural model assessment: Does my theoretical model fit the data? How good is my proposed representation of the relationships among the constructs? Is there another configuration that is better?

The starting point for assessing the structural model is β and R^2 values. The effort expended in developing the rationale for a model that contains mediating variables and moderating variables, will be rewarded in the structural model assessment. Without clear thinking with regards to the proposed model, structural model assessment may be

[1] This article contain three sections, two of which may be of keen interest to someone unfamiliar with PLS. Pages 284 to 297 explicate the PLS algorithm in fairly lay terms. Relevant to the point at hand, pages 298 to 310 go through the two categories (and numerous steps) of assessing PLS results.

Validity Type	Criterion	Description	Literature
Unidimen-sionality	Exploratory factor analysis (EFA)	Measurement items should converge in the corresponding factor so that each item loads with a high coefficient on only one factor, and this factor is the same for all items that are supposed to measure it. The number of selected factors is determined by the numbers of factors with an Eigenvalue exceeding 1.0. An item loading is usually considered high if the loading coefficient is above .600 and considered low if the coefficient is below .400.	Gefen and Straub (2005), Gerbing and Anderson (1988)
Internal consistency reliability	Cronbach's alpha (CA)	Measures the degree to which the MVs load simultaneously when the LV increases. Alpha values ranges from 0 (completely unreliable) to 1 (perfectly reliable). Proposed threshold value for confirmative (explorative) research: CA > .800 or .900 (0.700). Values must not be lower than .600.	Cronbach (1951), Nunally and Bernstein (1994)
Internal consistency reliability	Composite reliability (CR)	Attempts to measure the sum of an LV's factor loadings relative to the sum of the factor loadings plus error variance. Leads to values between 0 (completely unreliable) and 1 (perfectly reliable). Alternative to Cronbach's Alpha, allows indicators to not be equally weighted. Proposed threshold value for confirmative (explorative) research: CA > .800 or .900 (0.700). Values must not be lower than .600.	Werts et al. (1974), Nunally and Bernstein (1994)
Indicator reliability	Indicator loadings	Measures how much of the indicators variance is explained by the corresponding LV. Values should be significant at the .050 level and higher than .700. For exploratory research designs, lower thresholds are acceptable. The significance can be tested using bootstrapping or jackknifing.	Chin (1998b)
Convergent validity	Average variance extracted (AVE)	Attempts to measure the amount of variance that an LV component captures from its indicators relative to the amount due to measurement error. Proposed threshold value: AVE > 0.500.	Fornell and Larcker (1981)
Discriminant validity	Cross-loadings	Cross-loadings are obtained by correlating the component scores of each latent variable with all other items. If the loading of each indicator is higher for its designated construct than for any of the other constructs, and each of the constructs loads highest with its own items, it can be inferred that the models' constructs differ sufficiently from one another.	Chin (1998b)
Discriminant validity	Fornell-Larcker criterion	Requires an LV to share more variance with its assigned indicators than with any other LV. Accordingly, the AVE of each LV should be greater than the LV's highest squared correlation with any other LV.	Fornell and Larcker (1981)

Figure 5: Assessment of Reflective Measurement Models - Reproduced with permission from Urbach & Ahlemann (2010, Table 4), this table provides a checklist for the steps of measurement model assessment, with description of each step.

little more than a 'fishing expedition'. Each path (and each non-path) can be a separate hypothesis. Alternative models can be tested, or models for competing hypotheses.

CB-SEM and PLS differ to some extent with respect to structural model assessment. CB-SEM provides fit indices, so that two models can be directly compared to one another, or two datasets can be compared on the same model. The absence of fit indices in PLS gives pause to many researchers familiar with CB-SEM. It is incorrect to assume however, that just because PLS doesn't output fit indices, PLS is a second-rate technique. The ability to propose and to critique a model neither requires, nor solely rests, on reporting fit indices.

PLS is an excellent tool for testing multiple mediation and moderation, including three-way interactions.

PLS in general, and SmartPLS in particular, make the testing of multiple mediation very straightforward. Consider for a moment the model presented in Figure 6. There are three different paths from Y to X. The first is from Y→M1→X. The second is Y→M2→X. The third is Y→M1→M2→X.

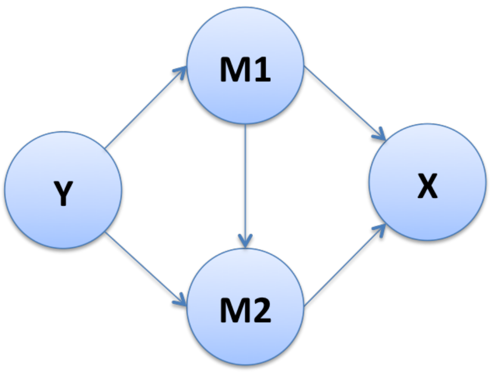

Figure 6: An Example of Multiple Mediation - A four construct model, exemplifying multiple mediation.

SmartPLS provides statistical significance testing for each of these three paths, as well as the combined 'total effect' through all possible paths from Y to X. The traditional notion of mediation testing using a Sobel test doesn't apply easily here[1]. However, by looking first at a model of only Y→X, and comparing the β and R^2 value to the full

[1]For models with simple mediation, the PLS output contains the information required for a Sobel calculator, to determine statistically significant mediation.

model in Figure 6, it is possible to get an indication of the extent of mediation via all three paths. Alternative models that systematically remove paths from the full model can provide even further insight.

What about moderation[1]? I include moderation in models throughout this thesis, using two different approaches to testing moderation. The first, and easiest to implement, is the product-indicator approach. SmartPLS provides a very efficient way to create the interaction product, and statistical significance testing is provided via the bootstrapping procedure. Furthermore, structural model parameters are reported for the interaction path, and are assessed along with the rest of the model.

A second way of testing moderation is via a technique called the PLS Multiple Group Analysis (Henseler, 2007; Henseler et al., 2009, PLS-MGA). I provide the details of implementing this technique in Chapter 5 on page 254, where I use it for the first time in this thesis. An overview is in order here though.

The first step of a PLS-MGA involves creating sub-datasets that partition the full dataset into groups (i.e. one dataset for males, and another for females). After verifying the measurement model, the structural model is output for both datasets and path coefficients are directly compared across groups. The test for group differences requires the use of an excel spreadsheet, but is nevertheless based on a bootstrap procedure, and thus is non-parametric.

What about when the models for two groups differ to a great extent? Take for example a full model with say, 10 constructs and 15 active paths. Now imagine that when the dataset is split into groups (again, think one for males and another for females), the model for males is reduced to only 4 constructs and 6 paths, while the model for females is reduced to 7 constructs and 11 paths. Imagine further that these models have only 4 paths in common. In this case, sex is acting as a moderator, and a PLS-MGA analysis can test for differences in all of the paths. Differences in the holistic set of constructs and paths provides a qualitative interpretation of differences that are empirically evidenced. Testing for such extensive moderation efficiently using more traditional techniques would be quite laborious. Direct comparison of fit indices in CB-SEM may be problematic for given the differing size and complexity of the models for each group.

[1]A in-depth treatment of moderation in PLS can be found in Henseler & Chin (2010).

I mentioned above that PLS could handle three way interactions with ease. In this case a PLS-MGA test for two different groups whose models contain an interaction term created via the product-interaction approach provides a relatively efficient test of a three-way interaction. The interpretation of the sign and magnitude of the interaction terms is usually best accomplished using graphing of means for the various sub-groups. If the path coefficients of interaction terms for the two groups are deemed significantly different from each other, there is a three-way interaction present.

These examples are admittedly brief. Models in chapters throughout this thesis will demonstrate these points more extensively.

SmartPLS, the software I use to implement PLS, is easy to use and well-supported.

SmartPLS has an intuitive graphical user-interface with extensive, yet neatly-organised output. Models are built in much the same way as one would go about building a powerpoint slide: Drop-down menus provide the user with a 'mode' to insert constructs, and a 'mode' to connect the constructs with arrows. Right-clicking on an construct provides a context-sensitive menu of options where it is possible to, for example, create interaction terms or hide or show the indicators of a particular construct.

The software is thoughtfully designed with the user experience in mind. SmartPLS is in it's 2nd generation build, and a 3rd generation is expected soon (REFERENCE to email, personal communication).

There is a large and helpful user community. Once registered for SmartPLS, a user has access to a web-based forum where questions can be posted for others to respond to, and a history of these questions is retained for searching by other users.

The PLS Algorithm

The PLS algorithm is widely published. A very brief summary of it is provided by Henseler et al. (2009, p. 287) and also Urbach & Ahlemann (2010, p. 14). A more extended explanation is provided in the first two chapters of Vinzi et al. (2010) and another good explanation, though quite mathematical, was written by Tenenhaus, Vinzi, Chatelin & Lauro (2005).

I reproduce a short section from Urbach & Ahlemann (2010, p. 14) here, which succinctly describes the PLS algorithm. I have added footnotes to assist with some terminology and concepts.

> The main procedure consists of two steps. The first step is called outside approximation and estimates all LVs[1] in the form of weighted aggregates of the MVs[2]. In a first iteration, this estimation is achieved by allocating equal weights to each block of indicators[3]. Using these weights, LV scores are calculated for each of the cases. Further iterations calculate more appropriate weights, which are based on the empirical data and the proxies for all LVs obtained from the next step. The calculation of the weights is done by means of regression[4]. The second step is called inside approximation and creates proxies for each endogenous LV based on this LVs association with other, neighboring LVs. Once more, regression is used. The results of this regression are new LV proxies for the next iteration of this pair of outside and inside approximations. The algorithm stops applying a stopping rule when, for instance, the previous iteration has not led to a significant improvement of the LV estimates[5]. During the last phase of the algorithm, factor loadings, path coefficients, as well as validation measures, are computed.

Further Resources

A number of resources are readily available to learn more about PLS for anyone who wishes to adopt the technique into their own research. I discuss some of the more prominent resources below.

To begin running PLS, one needs to have a software program. SmartPLS is user-friendly, stable, and free to academics and students. The only requirement to activate the software is a registration code, which is quickly sent after joining the SmartPLS forum. The forum often advertises courses that are currently running, many in the

[1] Latent Variables

[2] Manifest Variables, also called indicators

[3] A 'block' is the set of indicators for a given construct.

[4] Regression is usually performed using ordinary least squares.

[5] I discuss the stop criterion in a footnote on page 326.

United States, Germany, and Australia. There are also courses delivered over the internet using a virtual classroom. Subscription to a mailing list will bring announcements directly to an individual's email inbox.

A highly recommended course is run by Geoffrey Hubona who teaches for Virginia Commonwealth University. An internet search should locate his most recent contact details. Courses currently offered range from from short beginner and intermediate courses (four online classroom meetings) to longer (twelve online classroom meetings, with homework for each session). The longer course culminates with a certificate in PLS modelling and covers advanced topics in PLS. I have completed all three of these courses and found them to be sufficiently instructive to acquire the competence and confidence to conduct PLS analyses, particularly the certification course.

An excellent, although advanced, reference is the *Handbook of Partial Least Squares* (Vinzi et al., 2010). It contains 33 chapters across 800 pages of empirical demonstrations of the applications and use of PLS. There are several earlier papers that may also be of interest, many of which I have referred to throughout this chapter. A few that I have yet to provide are below.

- Barclay, D., C. Higgins and R. Thompson (1995). The Partial Least Squares (PLS) Approach to Causal Modeling: Personal Computer Adoption and Use as an Illustration. *Technology Studies*, volume 2, issue 2, 285-309.
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Summary and Conclusion

Being tools, statistical techniques should be purposively chosen based on the constraints and objectives of a given situation. At times, descriptive statistics may suffice, and the reach of the tools in that category are sometimes underestimated. Often however, researchers turn to inferential techniques to inform hypothesis testing and conclusions. The statistics I use in Chapters 3 to 5 include descriptives (Counts, Means, Standard Deviations, Skewness, Kurtosis, Factor Analysis, and Principal Components Analysis) as well as inferential statistics based on three underlying distribution assumptions (χ^2 Tests, ANOVA, t-tests, Correlation, Multiple Regression). Each chapter also includes some modelling using Partial Least Square Modelling, which has no assumptions regarding underlying distributions.

It is my hope I've convinced the reader that the advantages of employing PLS in my analyses outweigh the effort required to learn how to verify my interpretation of the results. Again, this primer is only meant to assist the reader in comprehending the PLS results presented herein. However, I hope that this primer, combined with the results have piqued the interest of the reader to adopt the technique in his or her own research, where appropriate.

Further explanation of PLS, within context, is provided in the body of the thesis. Some more advanced techniques are presented, and guidance provided to the reader along the way.

Declaration

I herewith declare that I have produced this thesis without the prohibited assistance of third parties and without making use of aids other than those specified; notions taken over directly or indirectly from other sources have been identified as such. This thesis has not previously been presented in identical or similar form to any other examination board.

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SYDNEY, AUSTRALIA