BEHAVIORAL STRATEGY IN THE WILD: CONTRADICTIONS, DIVERGENCES AND EMPIRICAL EVIDENCE

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STATEMENT OF ORIGINALITY

This is to certify that the content of this thesis is my own work. This thesis has not been submitted for any other degree or purpose.

I certify that the intellectual content of this thesis is the product of my own work, and that all assistance received in preparing this thesis and all sources have been acknowledged.

Takhaui Kamzabek

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Chapter 3, titled "How Organisational Structure influences Underperforming business units: Recovery, Exit, and Corporate profitability" is lead-authored by Takhaui Kamzabek, who carried out the majority of the theoretical and methodological work.

Chapter 4, titled "From Mutual Forbearance to Multifrontal Rivalry: Conditional Limits to Strategic Restraint", is also lead-authored by Takhaui Kamzabek, who conducted the majority of the theoretical and methodological work.

In addition to the authorship attribution statements above, in cases where I am not the corresponding author of a published item, permission to include the published material has been granted by the corresponding author.

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June 2025

Letter from the supervisor

As supervisor for the candidature upon which this thesis is based, I can confirm that the authorship attribution statements above are correct.

Prof. Dan Lovallo,

June 2025

ARTIFICIAL INTELLIGENCE STATEMENT

During the preparation of the thesis the author used ChatGPT for the purposes of editing. The use of this generative AI tool includes sentence structure, spelling, grammar, and rewording. All AI-assisted content was subsequently reviewed by the author and professional editor (i.e., @editorialcollective.com.au) to check for errors, inaccuracies, and potential bias. The author, Takhaui Kamzabek, takes full responsibility for the submitted thesis and ensures the work is their own and has used generative AI within the parameters of use.

THESIS ABSTRACT

Since Powell, Lovallo, and Fox (2011) first introduced cognitive and social psychology to the study of strategic decision-making, the concept of "behavioural strategy" has evolved significantly. In the years that followed, a substantial body of research has examined a wide range of cognitive biases and investigated strategies to mitigate their effects. At this stage, it is crucial to evaluate whether behavioural strategy has moved beyond controlled experimental settings into real-world applications, to assess the effectiveness of debiasing mechanisms, and to explore its interaction with broader organisational theories. This thesis addresses these questions through one review paper and two empirical studies.

Specifically, Chapter 2, "Behavioural Strategy in the Wild," reviews the evolution of behavioural strategy and its application in addressing real-world challenges. It categorises debiasing techniques into three families (i.e., analytical, organisational and debate techniques) and examines their effectiveness across four domains: mergers and acquisitions (M&As), military intelligence, resource allocation, and capital projects.

Chapter 3, "How organisational structure influences underperforming business units: Recovery, exit, and corporate profitability", empirically investigates how corporate partitioning (how businesses/segments are grouped within a firm) influences firms' commitment to underperforming business units and the outcomes of such commitments. Specifically, I show that there is an inverted U-shaped relationship between the number of segments within a firm and the likelihood of recovery for loss-making segments. This chapter contributes to the literature on Escalation of Commitment, the Behavioral Theory of the Firm, and Corporate Socialism.

Chapter 4, "From mutual forbearance to multifrontal rivalry: Conditional limits to strategic restraint", explores the dynamics of multimarket contact (MMC) and the conditions under which firms competitive arousal overrides mutual forbearance. Specifically, we show that mutual forbearance (i.e., tendency to refrain from aggressive competitive moves across shared markets)

often breaks down when there are more overlaps, when the nonoverlapping segments are highly profitable and when the industry is growing. Under these conditions, tacit collusion unravels due to rivalry-driven motivations that override the predictions of rational economic models, leading firms to make aggressive investments in each other's key markets.

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CHAPTER 1 INTRODUCTION

This thesis, inspired by behavioural economics, acknowledges that humans do not possess the unlimited cognitive capabilities assumed by neo-classical economics (Thaler, 2016). Instead, fields like strategic management now consider the impact of judgment and decision-making biases on strategy. The concept of "behavioural strategy" seeks to merge cognitive and social psychology with strategic management, incorporating more realistic assumptions about human cognition, emotions, and social behaviour into organisational strategy (Powell et al., 2011). This approach enhances both theoretical and empirical research, as well as practical applications in strategic management.

Since its introduction, behavioural strategy has gained momentum, especially in identifying managerial biases (see recent review by Rau & Bromiley, 2025) and heuristics (reviewed by Vuori et al., 2024). For instance, studies have revealed partition dependence in resource allocation (Bardolet et al., 2011), persistent optimism and a range of planning-related biases in project management (Flyvbjerg, 2021), and executive susceptibility to biases such as sunk cost fallacy, in-group favouritism, and stereotyping (Muntwiler et al., 2025); and anchoring bias in M&A decisions (Malhotra et al., 2015).

However, much of this work, particularly on debiasing mechanisms, remains confined to controlled experimental settings, limiting our understanding of how behavioural tools or interventions function in real-world strategic contexts. In addition, behavioural insights have yet to be meaningfully integrated with other theoretical perspectives grounded in the empirical study of firm behaviour. This thesis addresses both of these limitations by examining corporate resource allocation decisions, specifically, the persistence of nonoptimal investment behaviours across three chapters (Chapters 2, 3, and 4). Chapter 2 investigates the use of debiasing mechanisms and behavioural interventions within organisational settings. Chapters 3 and 4 extend the analysis by exploring how behavioural strategy intersects with firm-level theories: Chapter 3 examines the

interplay between escalation of commitment and other firm-level mechanisms in investment decisions involving underperforming business units, while Chapter 4 analyses behavioural departures from mutual forbearance in the context of multimarket competition.

Specifically, *Chapter 2* - "Behavioural Strategy in the Wild" examines the real-world application of behavioural strategy in organisational settings. The study focuses on how behavioural insights have been applied in resource allocation, as well as in other high-stakes domains such as military intelligence, M&A deal-making, and capital project planning—highlighting the most salient cognitive bias in each context. The paper then classifies three broad families of debiasing mechanisms—*analytical*, *organisational*, and *debate*—and proposes how various techniques have been, or could be, implemented under each mechanism.

Building on this foundation, *Chapter 3* explores the organisational antecedents of de-escalation of commitments from loss-making business units, with a particular focus on *corporate partitioning* (i.e., how firm activities are grouped within a firm). Experimental evidence suggests that firms that group businesses into smaller, more finely partitioned units are more likely to cut losses and withdraw support from underperforming units (e.g., Burson et al., 2013; Harvey & Victoravich, 2009; Kwong & Wong, 2014; McCain, 1986; Northcraft & Neale, 1986). Yet, evidence from actual firms points to a more nuanced reality: multibusiness structures can just as easily facilitate continued investment in struggling units. In particular, two competing logics, aspiration-driven recovery (Posen et al., 2018) and corporate socialism (Sengul et al., 2019) offer distinct explanations for why firms choose to persist rather than divest.

This chapter reconciles these perspectives by developing an integrative lens that bridges escalation of commitment (which highlights the sunk cost fallacy bias), behavioural theory of the firm (which emphasises aspiration-driven support), and internal capital allocation (which underscores agency issues), as each framework relies on distinct underlying mechanisms. We identify *corporate partitioning* as a critical factor influencing how firms respond to underperformance and as a key to explaining divergent findings in the literature on firms' responses to loss-making

units. Specifically, we find that firms are more likely to retain and attempt to recover underperforming units when partitioning is moderate (i.e., measured at the 4-digit SIC level), whereas finer partitioning (more than five segments) encourages a winner-picking approach. We conclude that finer corporate partitioning offers a structural advantage in curbing commitment to failing units and promoting more disciplined resource reallocation.

Chapter 4 extends the logic of competitive arousal by examining how *multimarket contact* (MMC) affects the stability of tacit collusion. While prior theory suggests that firms with market overlaps restrain competition to avoid cross-market retaliation (Bernheim & Whinston, 1990; Edwards, 1955), our findings highlight three conditions under which the relationship between the MMC and mutual forbearance is not clearly established.

First, although MMC is thought to foster herding behavior, where firms imitate rivals' entries in pursuit of tacit coordination (Dekeyser et al., 2021; Feinberg & Larson, 2024; Hsieh & Vermeulen, 2014; Hughes & Oughton, 1993; Lin & McCarthy, 2023; Schmitt, 2018), several studies have challenged this view, suggesting that extensive overlap may instead provoke aggressive responses, as frequent encounters between rivals heighten competitive arousal (e.g., Baum & Korn, 1999; Fuentelsaz & Gómez, 2006; Haveman & Nonnemaker, 2000; Klein et al., 2020). Our results support this latter view, showing that excessive overlap heightens competitive tension. In particular, firms may interpret rivals' moves as territorial invasions, instances where firms seek to preserve exclusive control over certain markets (Bhattacharjea & Sinha, 2015; Byford & Gans, 2014) as firm want to retain some market exclusive to them. In response to greater overlap, firms often retaliate with aggressive investments in their rivals' key markets.

Second, even when territorial boundaries are respected, i.e., rivals avoid entering some of each other's markets, it remains unclear how firms coordinate investment decisions between overlapping (i.e., those shared with multimarket rivals) and non-overlapping markets. The dynamics of resource allocation across these domains are underexplored and may hold the key to understanding when firms choose to escalate or restrain competition. Our findings show that firms

frequently reallocate profits from non-overlapping segments to fund aggressive investments in shared industries, suggesting a strategic motivation to assert dominance over multimarket rivals.

Third, the effect of rapid market growth on mutual forbearance remains inconclusive. While earlier studies consistently found that firms tend to reduce investments in growing markets to avoid triggering retaliation (Bernheim & Whinston, 1990; Sengul & Gimeno, 2013), more recent work has begun to challenge this assumption, particularly in contexts where technological booms (Hsu & Cohen, 2022; Roy & Sarkar, 2022). Our findings further show that when growth occurs in markets important to rivals, the stakes of competitive engagement increase, encouraging firms to abandon mutual forbearance.

Taken together, *Chapter 4* reveals that while MMC is traditionally viewed as a stabilising force, it can, under certain conditions, fuel intensified rivalry. Moreover, we show that such competitive aggression can ultimately push firms out of some markets.

Overall, this thesis is structured as a three-paper compilation. *Chapter 2* presents a theoretical review that synthesises insights from behavioural strategy, while *Chapters 3 and 4* build on this foundation through empirical studies that examine how organisational and competitive structures influence firm behaviour.

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BEHAVIORAL STRATEGY IN THE WILD

"*A behavioral approach to strategy – what's the alternative?*" (Levinthal, 2011, p. 1517)

Introduction

This provocative title of Levinthal's (2011) paper quoted above might be a play on Charlie Munger's famous quote: "How could economics not be behavioural. If it isn't behavioural, what the hell is it?" (Munger, 1995, p. 1). These quotes point to a conceptual transition from an ideal of rational choice to an acceptance of the boundedness of people. Boundedness is where real people do not have the cognitive capabilities to live up to neo-classical economic theory's requirements of rational choice (Simon, 1955), according to which rational agents have well-defined preferences, unbiased beliefs, make optimal choices based on these beliefs and preferences and act in their own self-interest (Thaler, 2016).

Recognising our boundedness, fields such as economics, finance, decision theory and others, including strategic management, now consider the impact of judgment and decision-making. In the context of strategic management, Lovallo and Sibony (2010, p. 2) adopt the term "behavioural strategy," arguing for "behavioural strategy" in practice, asserting that "left unchecked, subconscious biases will undermine strategic decision making." Gavetti (2012), Greve (2013) and Powell et al. (2011) have extended Lovallo and Sibony's work. Gavetti (2012) argues that behavioural failures of rationality, plasticity and shaping limit firms' pursuit of cognitively distant opportunities. His key insight is that "superior opportunities tend to be cognitively distant" (p. 269), yet must be attainable to be strategically relevant. From this he suggests that strategic leaders need to acquire the skills that bring cognitively distant opportunities nearer for themselves and other stakeholders (Gavetti, 2012). Greve (2013) discusses four levels of bounded rationality in strategy: first, firms are inclined to repeat past strategies without examining the consequences; second, firms incorrectly respond to feedback because of false assumptions of causality; third, firms infer that successful strategies of others will be good for them; and fourth, the most rational of the strategies, albeit still inclined to suffer from

bounded rationality, is where firms develop strategies based on their predictions of the actions of others.

Powell et al. (2011, p. 1371) build on rich theoretical foundations (from behavioral decision theory, political theory, organizational theory, social cognition theory, management perception, sense-making, cognitive schema, language, meaning and enacted environments) to set out their objectives for behavioral strategy: "Behavioral strategy aims to bring realistic assumptions about human cognition, emotions, and social behavior to the strategic management of organizations and, thereby, to enrich strategy theory, empirical research, and real-world practice." Powell et al. (2011, p. 1382) engage with Levinthal's (2011) question, saying: "we need models that solve the problems faced by thinking and feeling human beings, and this requires a robust and dynamic field of behavioral strategy."

We respond to Powell et al.'s (2011) call for models to solve real problems faced by real people. We refer to these models as debiasing techniques, which we categorise as: analytical, debate and organisational. We discuss business managers' and political or military leaders' strategic decisions in four real-world settings, where, in the absence of debiasing, we are likely to encounter problematic decision making due to confirmation bias, over-optimism, inertia due to anchoring, and the planning fallacy. In each of these four settings we describe a failure case and discuss the behavioural biases involved, focusing on one major bias and its mechanism. We then introduce a relevant debiasing technique and demonstrate it has been used successfully to debias in a similar setting.

Military intelligence and confirmation bias

"If you torture the data long enough, it will confess to anything" Ronald Coase.

The USA's devastating handling of the Vietnam war has been extensively documented. Here, we focus on lesser-known insights to illustrate how confirmation bias, acting at three levels, influenced U.S. policy and contributed to its Vietnam debacle. At the highest level, we show how U.S. Secretary of Defence, Robert McNamara, fell victim to poor reasoning. At the intermediate level, we discuss the RAND Corporation (RAND), a think tank and how its intelligence process failed. And, at the

lowest level, we explore how two well-respected senior intelligence analysts formed opposite interpretations of the same data.

Failure case

McNamara was regarded as a brilliant manager in the decades before and after the Vietnam war, but his emphasis on rational analysis based on quantifiable data led to grave errors (Rosenzweig, 2010). Specifically, data that was difficult to quantify, such as qualitative intelligence on intangibles such as motivation, hope, resentment or courage, tended to be overlooked (Rosenzweig, 2010), despite the potential for this information to play a critical role in US war strategy. McNamara's failings offer some insight into how management thinking has progressed (Rosenzweig, 2010). We now know that people are not the rational creatures suggested by neo-classical economics but exhibit systematic biases of judgment (Rosenzweig, 2010). We also know that organisational processes have their own dynamics – such as the escalation of commitment to a losing course of action, and the tendency to silence dissenting views – that can lead to flawed decisions.

McNamara's intelligence briefings came from, among other sources, RAND, which advised the US Government during the Vietnam War, including via its Viet Cong Motivation and Morale Project, established to examine the organisation, operations, motivation and morale of the Viet Cong and North Vietnamese Army (Donnell et al., 1965). Yet RAND as an organisation, which prided itself on objectivity, also succumbed to bias.

Leon Goure and Konrad Kellen were two well-respected RAND senior intelligence analysts. Goure was born in 1922 in Moscow, went into exile in Berlin to escape Lenin's liquidation of the Mensheviks, later fleeing to the USA to escape the Nazis (Elliott, 2010). He became a Soviet specialist in RAND's Social Science Department, gaining fame as an expert on Soviet civil defence (Elliott, 2010). Goure led RAND's Viet Cong Motivation and Morale Project, which interviewed hundreds of defectors and prisoners-of-war and produced 62,000 pages of interview transcripts (Gladwell, 2016). These transcripts were a key source of intelligence, however, a member of RAND's Social Science team said that the transcripts could "support anybody's perspective on anything" (Elliott, 2010, p. 165).

Goure had a profound dislike and distrust of communism. When Goure read the transcripts, his view was that the Viet Cong had lost the "fight for hearts and minds" (Elliott, 2010, p. 164). Based on his earlier work, he was allegedly already an advocate of airpower as a weapon of counterinsurgency (Elliott, 2010). According to Gladwell (2016), Goure's background led him to believe that "if we just bomb some more, we'll destroy their will." This view was questioned by "a fair number of analysts […] convinced that Goure was interpreting selectively from the interviews" (Elliott, 2010, p. 125). Goure's behaviour is consistent with what Snyder calls the "ideology of the offensive" (Snyder, 2013).

To strike a balance and provide a broader base from which to draw inferences and discern trends regarding the Viet Cong, RAND brought in Kellen (Elliott, 2010), a Jewish man born in Berlin in 1913, who had escaped the Nazis. Kellen moved to the USA in 1935 and worked in US Army intelligence, where he dealt with prisoner interrogation material in Second World War and Korea and defectors from Eastern Europe (Elliott, 2010). Based on his reading of Viet Cong interviews, he told a colleague: "Prisoners and defectors tell you what they think you want to hear. These people, you can't get them to say anything critical of their regime" (Elliott, 2010, p. 231). Kellen concluded that they "could not be coerced" (Elliott, 2010, p. 231).

Goure and Kellen read the same interview transcripts and arrived at opposite perspectives. Gladwell (2016) sums it up: "That's how intelligence failures happen. It's not because someone screws up, or is stupid, or is lazy, it's because the people that make sense of intelligence are human beings, with their own histories and biases." As Kellen says, in his account of RAND's leadership (which might itself be biased): "I can only say that the people that I knew who talked a lot about scientific talk and scientific this and that were the most unscientific people you can imagine. They just picked somebody and if they agreed with him or he agreed with them, then he was an expert, and if he didn't agree with them, he was not an expert and they ruled it out" (Gladwell, 2016). In other words, RAND's leaders were subject to confirmation bias.

Of course, intelligence failures are not unique to Vietnam and their implications can be devastating. Military conflicts exact a substantial cost in lives, livelihoods, and dollars. The Afghanistan war cost the USA more than $2tn and almost 250,000 people have died as a direct result

(Crawford and Lutz, 2021). Intelligence failures happen in the market economy too. Central bankers' failure [1] to interpret signs of the impending global financial crisis is attributed to confirmation bias based on their frame of an efficient market hypothesis (EMH) worldview (Stiglitz, 2012).

What behavioural biases are at play?

Military intelligence is a key determinant of whether and how conflicts occur. Bar-Joseph and Levy (2009) describe seven sources of intelligence failures: a lack of information; a "noisy" environment (too much information, making it difficult to extract the signal); strategic deception (where one side deliberately deceives the other); individual psychology (including cognitive and motivational biases); small group dynamics (such as group-think); organizational behavior (leading to fragmentation or concentration of information); and politicization of intelligence (intelligence is deliberately aligned to policy preferences, for example, the claim of weapons of mass destruction in Iraq).

How does confirmation bias affect military intelligence?

Bar-Joseph and Levy (2009) recognise that many or all the above factors might be at play in an intelligence failure, but in the case of Israel's surprise at the Yom Kippur War they argue that the root cause of the failure was individual psychology. The director of military intelligence's (DMI) conviction that his own assessment was correct led him to conceal information about recent actions by the Egyptians and Syrians and not carry out orders to implement critical intelligence procedures (Bar-Joseph and Levy, 2009). The DMI's assumptions about Egypt's military strategy (Chen, 2016) caused him to dismiss evidence of an impending attack by Egypt because it was not consistent with his view (Chen, 2016).

There are many other examples of large-scale surprise attacks, which Dahl (2013) argues are not the result of an inability to detect the signal from the noise and/or an inability to connect the dots, but because specificity of tactical level intelligence is required and then policymakers must be receptive to that intelligence. Dahl refers to Heuer's (1999) analysis of how many intelligence failures are the result of cognitive biases and mindsets that are resistant to change. Developing a strong point-of-view and then not being receptive to disconfirming intelligence is a demonstration of confirmation

bias.

Nickerson (1998, p. 175) defines this bias as "the seeking or interpreting of evidence in ways that are partial to existing beliefs, expectations, or a hypothesis in hand." Others define confirmation bias as our tendency to discount disconfirming evidence (Kappes et al., 2020). Importantly, confirmation bias relates to "unwitting selectivity in the acquisition and use of evidence" (Nickerson, 1998, p. 175). In the real world, the line between "unwitting selectivity" and the deliberate marshalling of evidence to support one's case is often not clearly defined (Nickerson, 1998). Hence, it can be challenging to disentangle the cognitive bias (we see what we expect to see) and motivational bias (we see what we want or need to see) factors that lead to a judgment (Bar-Joseph and Levy, 2009; Nickerson, 1998).

What should we do about it?

Numerous debiasing techniques have been identified for each of the behavioural biases discussed in this article. In each section, we focus on just one technique. Table 2-1 outlines other debiasing techniques, categorised as organisational, debate and analytical techniques.

Red team/blue team is a debate technique for debiasing confirmation bias. Red teams are empowered to generate alternative perspectives to challenge strategic assumptions and plans (Zhang and Gronvall, 2020). Red teaming has been used by the military for more than a century and has also been used in the public and private sectors to better understand the interests, intentions and capabilities of rivals (Zenko, 2015b), for example, in capital project bidding (Heiligtag et al., 2017), investment decision making (Gatlin et al., 2017), improving R&D productivity (Smietana et al., 2015), terrorism defense (Zhang and Gronvall, 2020), cyber-security (Mirkovic et al., 2008) and even assessing survivability of space systems (Stokes et al., 2006).

Zenko (2015b, p. 17) writes that "An astonishing number of senior leaders are systemically incapable of identifying their organisation's most glaring and dangerous shortcomings." This occurs for two reasons: cognitive biases, including confirmation bias; and organisational biases, where employees become captured by the institutional culture (Zenko, 2015b). Zenko (2015b) describes three broad categories of red-teaming techniques: simulations, including "war games," designed to

model a diverse range of situations and ultimately spur decision-makers to respond to various scenarios; vulnerability probes, when a red team actively tests defensive systems and procedures to identify key weaknesses; and alternative analyses, where key assumptions or information quality are challenged by promoting unconventional thinking (Zenko, 2015b).

The red team (attackers) is pitted against the blue team (defenders) (Boyens et al., 2012), which typically must defend against real or simulated attacks over a significant period, in a representative operational context, and according to rules established and monitored by a neutral monitoring group (the white team) (Boyens et al., 2012). By applying fresh eyes on a complex situation or intentionally opposing a certain position, red teams can greatly improve the accuracy of forecasts (Zenko, 2015b).

Success case

Red teams can deliver impressive results, such as giving businesses a competitive edge, finding flaws and vulnerabilities in military intelligence and troubleshooting dangerous military missions in advance (Zenko, 2015b). The successful 2011 US Navy SEAL mission that killed Osama bin Laden used red team preparation that included the developing, testing and refining of strategies, thus enabling a response to an unforeseen situation, the crash of one of the two transport helicopters (Zenko, 2015b).

The red team responsible for the raid benefited from a decade of deliberate efforts by the CIA that were triggered by the unprecedented terrorist attacks of 9/11. Following 9/11, senior White House officials believed that there were additional plots against the US The Director of Central Intelligence George Tenet formed a group of contrarian thinkers to challenge conventional wisdom in the intelligence community (Zenko, 2015a). This group, known as the Red Cell, is a semi-independent unit devoted to "alternative analysis," including techniques like "what ifs," Team A/Team B exercises, and premortem analysis Klein (2007), which can identify holes in a plan, model an adversary to understand their weaknesses or consider in advance all the conceivable ways a plan can fail and thereby mitigate these risks (Zenko, 2015a).

By design, the initial Red Cell focused on the bin Laden raid did not include any terrorism

experts and only had one Middle East specialist (Zenko, 2015a). Instead, members were individually selected on the basis of being creative, analytically fearless, excellent writers, deeply knowledgeable about history and world affairs and able to work in a team (Zenko, 2015a). Analysts typically served on the Red Cell for a period of three months, to keep participants fresh and to immerse as many analysts as possible in its techniques (Zenko, 2015a).

A red-team approach has also been shown to create value in a business context, as illustrated by Warren Buffet, who actively seeks contrary viewpoints (Gatlin et al., 2017), including assigning two independent groups (red team and blue team) to represent opposing sides on potential acquisitions and they are paid a bonus if their views prevail (De Smet et al., 2019). The marginal cost of these two viewpoints can often be justified by the magnitude of these deals. Buffet provides a useful reminder of how we might think about confirmation bias: "You don't ask the barber whether you need a haircut" (Buffett, 1994).

Mergers and acquisitions deal-making and over-optimism

"Thinking rosy futures is as biological as sexual fantasy" (Tiger, 1979, p. 35)

It is not just confirmation bias that should concern us when undertaking acquisitions – numerous behavioural biases contribute to a generally poor track record in mergers and acquisitions (M&A) transactions. Here, we focus on over-optimism.

Failure case

In April 2014, the Australian department store business David Jones (DJs) was bought by South African-based Woolworths Holdings (WHL) for AUD 2.1bn. Recognising that it was buying a struggling business, WHL's chief executive officer (CEO) announced that WHL could triple

Table 2-1 Summary of debiasing techniques applicable to the four behavioural biases covered in this paper and categorised by organisational, debate, and analytical

Biases	Organisational techniques	Debate techniques	Analytical techniques
Confirmation bias	**Two-level governance** – A governance structure to challenge the decision team's investment decisions. Having two layers of decision helps catch flawed judgments that make it past the decision team (Sibony et al., 2017).	**Red team / blue team** – Two separate teams develop competing recommendations on a proposal. One group – a blue team – investigates with a view to proposing the project or investment, while another – the red team – builds a case against the project or investment. The independent decision maker decides based on the opposing cases presented (Heiligtag et al., 2017; Zhang & Gronvall, 2020). **Mandatory alternatives** – A rule whereby every team or individual proposing a project for approval is required to propose not one, but two. As a result 'yes/no' or 'whether or not' questions are outlawed and it becomes normal, not exceptional, to see projects being rejected (Sibony, 2020). **Advance checklist "What would need to be true"** – In advance of the facts of the proposal being known and discussed the decision makers agree on the criteria they would require to be true in order for the decision to be made (McGrath & MacMillan, 2009).	**Qualitative scenario analysis** – Informs decisions by developing a set of qualitative, representative scenarios of alternative futures and identifying the likely consequences of the decision under consideration (Clemons, 1995).
Over-optimism	**Mediating Assessment Protocol** – Incorporates reference class forecasting and other debiasing practices, such as postponing the use of intuition, using relative scales, and benefiting from the wisdom of the crowd (Kahneman et al., 2019).	**Premortem** – The leader asks the group to imagine themselves in the future in which the project they are considering has been a total failure. The group is asked to consider the reasons that it went wrong. This serves to elicit weaknesses and risks (Klein, 2007). **Consider the opposite / "What if we're wrong"** – Consideration of alternative hypotheses by asking "What are some reasons that our initial judgment might be wrong?" (Larrick, 2004).	**Test, learn, adapt** – A systematic policy of piloting concepts in advance of full roll-out. Instead of trying to predict the future, test a potential solution actively by trying it on a small scale (Reis, 2011; Smit & Lovallo, 2014). **Periphery scan** – Include learning from the past (e.g., What have been our past blind spots? What is happening in these areas now?), examining the present (e.g., What are your mavericks and outliers trying to tell you?) and envisioning new futures (e.g., What emerging technologies could change the game?) (Day & Schoemaker, 2005).

Biases	Organisational techniques	Debate techniques	Analytical techniques
Anchoring / inertia	**CEO piggybank** – An approach to budgeting in which a large contingency fund is set aside to seize opportunities, whether to nurture existing businesses with additional capital or to acquire new assets at knockdown prices (Bradley et al., 2018; Lovallo et al., 2020).	**If this was your money** – An exercise in which each participant is asked to allocate funds, assuming this is their individual portfolio, not corporate funds. **Reanchoring** – Debate on cases where there is a large discrepancy between history (i.e., this year's target) and model, and to allow a discussion in which large amounts are reallocated. Done using an outside set of forecasts (e.g., competitor benchmarking) (Lovallo & Sibony, 2012).	**Inertia benchmarking** – Measures the correlation between the percentage of resources each cell (e.g., division) in a portfolio received in the most recent year and what it received in previous years. This draws attention to whether resource allocation is too stable (Hall et al., 2012).
Planning fallacy	**Trip-wires** – Development of an early warning system that triggers one to act when certain pre-defined conditions are met (Soll et al., 2015). **Incentives / motivation** – Establishes financial and non-financial reward policies for an accurate estimate of project and also establishes punishments for inaccuracies (Flyvbjerg, 2009). **Share financial responsibility** – Budget, cost over-runs, and benefit shortfalls are shared between proposing and approving agencies. This reduces the agency problem driver of the planning fallacy (Flyvbjerg et al., 2009).	**Additional downside** – The rule of thumb to apply this approach is to "Add 20-25% more downside to the most pessimistic scenario" and then decide whether the plan is still viable (Belsky & Gilovich, 2010). **Unpacking a task** – An exercise in which participants break down multifaceted tasks into precise subcomponents. Unpacking helps to consider under-counted components, and will provide a longer and more accurate forecast (Kruger & Evans, 2004).	**Reference class forecast** – A method of forecasting based on a sample of relevant comparable cases. Requires explicitly creating a large enough "reference class" (often from the experiences of other companies) (Lovallo & Kahneman, 2003). **Similarity-based forecasting** – An application of Reference Class Forecast where reference classes are not weighted equally but by similarity (Lovallo et al., 2012).

profitability in five years and said: "we can transform this business" (Australian Associated Press, 2014). But in 2018 and 2019, WHL wrote off a total of AUD 1.2bn of DJs, more than half of the deal value. With these impairments, the strategic rationale was in tatters.

There are three reasons why over-optimism appears to have been at play here. First, the acquisition was made with a 25% premium and was seen by analysts as expensive (Hayward and Hambrick, 1997). Second, earnings were overestimated: The earnings margin expectation of at least 10% became 4% in actuals. The FY19 expectation was also 10%, yet the actuals were a mere 2%. WHL revised down their guidance for FY20 to 7%–9%, but still only delivered 2%. Third, this repeated failure to meet expectations is consistent with overconfident CEOs being less responsiveness to corrective feedback (Chen et al., 2015).

While M&As are important vehicles for strategic growth (Lubatkin, 1987), they often fail to deliver intended performance improvements (Garbuio et al., 2010). Vinogradova (2021) shows that capital markets still perceive acquisitions as value destructive, whereas Rehm et al. (2012) finds that large acquisitions have only a 44% chance of delivering returns above the industry average and show a negative median excess total return to shareholders. Acquisitions with the most value destructive prospects are "large deals," like the case of WHL–DJs (Rehm et al., 2012). Martin (2016) calls M&A a "mug's game," reporting that 70%–90% of acquisitions are abysmal failures, yet M&A deals continue to be pervasive (Weber, 2018). The prospects for "programmatic deals" are far better, delivering an average of 4.5 per centage points greater excess total returns to shareholders than "large deals" (Rehm et al., 2012).

What behavioural biases are at play?

Researchers identify rational behaviours, such as agency issues (Eisenhardt, 1989; Jensen, 1986), where managers may pursue their own objectives at the expense of shareholder's interests, as one of the reasons that M&A deals are value destructive. Stock-based compensation means that CEOs can benefit substantially from even failed acquisitions (Martin, 2016). Other drivers are accounting regulatory changes following the global financial crisis making acquisitions more

attractive (Martin, 2016), and Yoo and McCardle (2020) "valuator's curse", which provides a rational explanation for the over-valuation of acquisitions.

Researchers also identify non-rational behaviours, driven by cognitive biases, across the M&A lifecycle (Garbuio et al., 2010). Garbuio et al. (2010) note empire building and the lemming effect during target pursuit, as well as confirmation bias, external advisors' role-conferred bias, over-optimism and the planning fallacy. They also highlight the role of the availability heuristic during preliminary due diligence, the winner's curse during the bidding phase, and anchoring and adjustment and the sunk-cost fallacy during final due diligence.

How does over-optimism affect M&A deals?

Warren Buffett likened acquisitions to the fairy tale *The Frog Prince*, where the corporate acquirer is a beautiful princess and the acquisition target the frog, which can be turned into a handsome prince with a kiss—or in this case, over-payment. Buffett (1981) view of this over-optimism— "We've observed many kisses but very few miracles"—finds robust theoretical and empirical support.

From Roll (1986) we learn that managers are subjected to strong pressure to maintain high performance and that, coupled with hubris, this drives risk-seeking behaviours. The predicted consequence for M&A is that bidding managers over-estimate their ability to manage the target firm and hence over-pay. Hayward and Hambrick (1997) offer empirical support for this theory, finding losses in acquiring firms' shareholder wealth following an acquisition, with the greater the CEO hubris and acquisition premiums, the greater the shareholder losses. Park et al. (2018) provide further empirical support in their analysis of CEO hubris in Korean firms. Billett and Qian (2008) support Roll's theory, finding that CEOs become over-confident after a successful acquisition, and therefore more likely to follow it with acquisitions that negatively impact their firm's stock. Malmendier and Tate (2008) also find that over-confident CEOs over-estimate their ability to generate returns, over-paying for target companies and undertaking value-destroying mergers. Over-confident CEOs also tend to complete more deals (Hwang et al., 2020) and hence

the problem is amplified.

What should we do about it?

A rich variety of techniques exist to debias over-optimism. Some of these are displayed in Table 2-1. We choose to focus on Mediating Assessments Protocol (MAP), which is both recent and promising. MAP is a meta-debiasing technique incorporating reference class forecasting[1] (RCF) and other debiasing practices, such as postponing the use of intuition, using relative scales, and benefiting from the wisdom of the crowd (Kahneman et al., 2019). It is based on research relating to the job interview, essentially treating a strategic decision like a job candidate. The research outlines the value of a structured process that identifies key traits, each of which is independently evaluated and serve as inputs into the overall decision, which is delayed until all these inputs have been gathered (Kahneman et al., 2019).

Success case

Kahneman et al. (2021) demonstrate the use of MAP in a confidential case where an acquisition is assessed by a private equity firm, following six key steps: first, structure the decision into a set of mediating assessments; second, whenever possible conduct the mediating assessment using the "outside view" (defined as simple statistical analysis of analogous efforts completed earlier (Lovallo & Kahneman, 2003)); third, keep the assessments independent of one another where possible; fourth, review each assessment separately; fifth, have participants make their judgments individually, then explain them to the group, then make a new estimate in response to the estimates and explanations of others[2]; sixth, make the final decision by holistically considering the mediating assessments and allowing intuition. This approach has now been adopted by several private equity firms.

1. Discussed in detail in the capital projects section of this paper.

2. Also termed the estimate-talk-estimate method or the mini-Delphi method.

Resource allocation and anchoring

"*Even if you are on the right track, you'll get run over if you just sit there.*" Will Rogers

M&A transactions, market entry strategies, capital projects, and any other strategic decisions require deliberate choices about the allocation of a firm's scarce resources. Here we examine behavioural biases, specifically anchoring, that contribute to inertia, which impedes a firm's resource allocation.

Failure Case

Nokia's success in the early 2000s was linked to the technology development for its Symbian-based handsets. At the end of 2007, the Symbian operating system had a market share of 65%, well above its competitors (Alcacer et al., 2014). However, the industry was shifting to software-focused ecosystems with the emergence of smartphones, such as the iPhone and Android smartphones manufactured by HTC, Motorola, Sony, Samsung. Internal bureaucracy meant that Nokia continued to concentrate on low-end feature phones and its patented Symbian operating system (Vuori & Huy, 2016). By 2010, Apple's Appstore hosted 300,000 apps, Android 130,000 apps, and Nokia just 30,000 apps (Vuori & Huy, 2016). Symbian had fallen to less than 5% market share when it was discontinued in 2012 (Han & Cho, 2016).

Failure to effectively allocate resources in the light of changing industry dynamics is not uncommon. Corporations have a tendency to focus on all areas of their business at once (also called peanutbuttering[3]), with typically little or no benefit (Bardolet et al., 2011; Bradley et al., 2018). Considering firm performance in tertiles, the most successful firms shifted more than half of their capital across their business units over a 15-year period, earning 30% higher total return to shareholders than the bottom tertile firms (Hall et al., 2012). A more recent study arrived at a similar conclusion (Lovallo et al., 2020).

3. Managers' tendency to allocate resources smoothly across the whole enterprise at a general level, despite opportunities in some areas being greater than in others (Bradley et al., 2018; Viguerie et al., 2008)

What behavioural biases are at play?

Inertia primarily occurs due to cognitive biases such as sunk cost fallacy, status quo bias, and anchoring in combination with corporate politics (Lovallo et al., 2020). Capital allocation failures also result from agency problems emerging from information asymmetry and incentive misalignments (Harris & Raviv, 1996). Of these various distorting factors, anchoring has been shown to be the most robust bias contributing to inertia (Tversky & Kahneman, 1974), and is especially evident in the most recent resource allocation decisions made by executives (Garbuio et al., 2011; Hall et al., 2012).

How does anchoring affect resource allocation?

Resource allocation decisions are impacted by anchoring for four reasons. First, last year's budget usually serves as a ready and justified reference point (Bardolet et al., 2011; Hall et al., 2012). Second, our initial judgments carry significant weight, and we do not react sufficiently to new information (Tversky & Kahneman, 1974). Third, anchoring is reinforced by loss aversion (Hall et al., 2012). Fourth, anchoring might occur because we value things more when they belong to us (Thaler, 1980), otherwise known as "endowed anchoring"(Garbuio et al., 2011). For example, Collinson and Wilson (2006), in a study of Japanese firms, reveal that established interdivisional and supplier relationships are over-valued because they are treated like an endowment, hampering firms' strategic flexibility.

What should we do about it?

A recommended debiasing technique is using a CEO piggybank, where a large contingency fund is set aside to seize opportunities, whether to nurture existing businesses or acquire new assets. This "changes the environment", enabling a more rational solution (Sibony et al., 2017; Soll et al., 2015b). The CEO piggybank helps managers become less anxious about under-performing units so fewer resources are directed to fixing them (Arrfelt et al., 2013). This method has been shown to reduce under-investment in over-performing business units (Arrfelt et al., 2013; Lovallo

et al., 2020; Lungeanu et al., 2016). Consequently the CEO piggybank provides more flexibility to change the composition of firms' assets (Bradley et al., 2018; Lovallo et al., 2020).

Success case

The CEO piggybank can be implemented by putting a certain percentage of the organisational portfolio up for sale each year, changing the burden of proof such that managers must justify the resources that they need and giving the CEO sole discretion to allocate a certain percentage of the company's capital. For example, as a leader of Exxon Mobil, Lee Raymond required executives to identify 3%–5% of their asset base for disposal, which helped identify non-strategic assets and prepare excess cash (Hall et al., 2012; Lovallo et al., 2020). When the CEO piggybank technique is applied, managers are instructed that a proportion of their assets are to be sold unless they can justify otherwise. This has been shown to minimise political infighting over budgets. In almost all cases, unit leaders in Exxon Mobil could not make a case for retaining their assets, which were then sold. Furthermore, allowing CEOs to allocate capital provides an opportunity to move the organisation more quickly toward what the CEO believes are exciting growth opportunities without first having to fight for resources with the company's executive committee (Hall et al., 2012).

A similar approach involves categorising the portfolio into different groups to determine allocation priority. For example, during Alan Lafley's leadership of P&G, the business was divided into three categories: "Future Stars," businesses with potential growth; "Local Jewels," businesses with strong brands in specific countries; and "Under-performers," businesses for divestiture (Wells and Danskin, 2014). Lafley presided over the discontinuation or sale of about 15 businesses a year between 2000 and 2009 (Lafley and Martin, 2013).

We cannot know whether the CEO piggybank had a causal impact on firm performance, but during Lafley's and Raymond's application of CEO piggybank, P&G and Exxon Mobil each doubled sales and more than quadrupled net profit (Lafley and Martin, 2013; The Economist, 2005).

Capital projects and the planning fallacy

"We learn from history that we learn nothing from history" (Shaw (1903/1948, p. 485)

Capital projects make large demands on a firm or government's resources. Here we explore the planning fallacy, which plagues capital projects. We show that techniques such as RCF are gaining traction in practice.

Failure Case

In 2008, California voters approved the construction of a 150-minute train route from Los Angeles to San Francisco at a cost of $40 billion with a construction period within 20 years. However, problems soon arose and the timeline was repeatedly pushed back, while the budget increased to a staggering $100 billion (Flyvbjerg & Gardner, 2021). A similar example is the construction of the Sydney Opera House, scheduled to finish in 1963 at a cost of $7 million, but delayed by 10 years and costing $102 million (Buehler et al., 1994).

This is a common experience for many business and public, with Standish Group's research on IT projects between 2005–2020 finding less than one-third were successfully completed on time and within budget, around 43–46% were delivered late and over-budget, or did not deliver all required features, while 19–21% were cancelled or never used (Johnson & Mulder, 2020). Flyvbjerg and Sunstein (2016) find that the average cost over-run in public projects ranged from 24% to 96%, and even over-runs of 100% or more are not uncommon (Flyvbjerg et al., 2009).

What behavioural biases are at play?

These statistics demonstrate that people often under-estimate task completion times and costs. Forecasting failures are primarily induced by cognitive bias like the planning fallacy, where planners inadequately adjust predictions despite previous projects taking longer than planned (Buehler et al., 1994; Flyvbjerg, 2009). Combined with anchoring bias and optimism (Lovallo & Kahneman, 2003), overly sanguine forecasts are triggered and the principal–agent dilemma magnifies the actual cost and time (Flyvbjerg et al., 2009).

How does the planning fallacy affect capital projects?

The planning fallacy, like over-optimism, is a manifestation of our "inside-view" behavior. However, it differs in that planners' optimism persists even in the face of historical evidence to the contrary (Buehler et al., 2010). By neglecting the past, we expect to finish our tasks before we actually do (Buehler et al., 2010), that is, we construct a narrative by focusing on cases that justify our optimism and fail to consider alternative scenarios (Buehler et al., 1994; Kahneman & Tversky, 1979).

What should we do about it?

RCF is an analytical technique that can help mitigate the planning fallacy. RCF gives managers an "outside view", so they can gather information from previous, similar projects, irrespective of the project's success. This prevents managers from focusing on similar, easily recalled projects that succeeded and are close in time and space to the decision at hand (Kahneman & Lovallo, 1993). By using realised outcomes of past projects, rather than manipulated estimates of the current project, RCF enables managers to forecast project estimates using more reliable, top-down estimates of the project's true costs, schedule, and benefits (Lovallo et al., 2012).

Lovallo and Kahneman (2003) offer a five-step process for RCF. First, select a set of past projects as the reference class, evaluating similarities and differences to determine which projects are most important to planning the current project. Ensure there are enough cases to be statistically valid and that the reference projects are comparable to the current project. Second, assess the distribution of outcomes to determine the probability distribution of actual outcomes in this reference class. This distribution will be used to determine the needed uplift for the new project. The decision maker should document the results in terms of relevant variables (e.g., total cost, schedule, etc.), showing extreme values, median values, and any clusters. Third, estimate your project's position in the distribution. Decision makers compare their projects with other reference class projects to arrive at an intuitive estimate, which is most likely biased, so the next two steps are applied to eliminate those biases. Fourth, assess the degree to which the type of information

available in this case allows accurate prediction of outcomes. Based on the historical precedent, estimate the correlation between reference class past predictions and outcomes to assess the reliability of the forecast made in step 3. Fifth, correct your intuitive estimate, which is likely to be optimistic, and adjust the mean based on the predictability analysis in step 4. The less reliable the prediction, the more the estimate must be regressed to the mean. Assume an intuitive construction cost projection of $4 billion for a rail project and that average reference-class rail projects cost $7 billion. Assume further that the correlation coefficient is estimated to be 0.6. The regression estimate of the construction cost is: $7B + [0.6 ($4B - $7B)] = $5.2B (Flyvbjerg et al., 2009).

Success case

RCF has been actively used in large transportation projects. For example, since 2003, it has become mandatory to apply RCF for infrastructure investments larger than £40 million in the U.K.. (Park, 2021), and is also a requirement in Denmark, Germany, Norway, Sweden, Switzerland, Netherlands, and the U.S. (Park, 2021). In order to be approved, all transportation projects in the U.K. over the last 20 years use the Infrastructure and Projects Authority database as a reference class, with a requirement to have a 50% probability of being completed within their original budgets. Before the adoption of RCF, the average level of cost over-run of large public projects in the U.K. was 38% (MacDonald, 2002). Park (2021) finds that, of 39 large U.K. projects planned and delivered subsequent to the RCF requirement, including road, rail, and building projects, the probability of successful projects completed within budget was 62%, surpassing the targeted probability (50%) by 12%, while cost over-runs were reduced from 38% to 5%.

The validity of RCF analytics has been tested in various other cases and settings, including a medium-sized finishing construction company (Batselier & Vanhoucke, 2016), a retrospective analysis of Hong Kong transportation (Flyvbjerg et al., 2016), the "Stuttgart 21" railway project (Steininger et al., 2020), and Turkish building projects (Bayram & Al-Jibouri, 2018).

RCF is perhaps the best illustration of the success of debiasing "in the wild." RCF, an analytical technique, is also being used as part of the emerging Mediating Assessments Protocol,

an organisational technique that was discussed earlier. That debiasing techniques are being combined seems appropriate because biases in the wild also often combine. For example, at the World Economic Forum in Davos, when central bankers were saying "who could have foreseen this?" in reference to the global financial crisis Stiglitz (2012), Joseph Stiglitz commented that the bankers' EMH training led them to frame the events as being consistent with EMH (framing effect and availability heuristic) and, given the variety and complexity of the information, led them to select information confirming their views and these biases, along with their overconfidence, led them to disregard information suggesting a bubble was forming (confirmation bias), resulting in their inaction (Stiglitz, 2012).

Conclusion

Is behavioural strategy coming of age? Has it moved from the lab into the wild? Do strategists recognise the need to take a behavioural approach to strategy, acknowledging their susceptibilities to behavioural biases?

In this paper, we have considered these questions by discussing debiasing techniques in different real-world settings. These techniques vary in their relative effectiveness; for example, analytical methods significantly outperformed debate methods in sales forecasts (Sanders and Manrodt, 2003); organizational techniques help managers make better decisions due to the engagement of System 1 (automatic and effortless) processes (Kahneman, 2011), which require less effort than analytical techniques that rely on System 2 (deliberate and effortful) processes (Kahneman, 2011; Liu et al., 2017); and, the debate technique is more popular among practitioners (Muntwiler, 2021).

Notwithstanding the above studies, we find a paucity of studies exploring behavioural strategy in the wild. We find no studies considering more complex real-world settings, where multiple biases are interacting. Future research should build on these "in-the-wild" studies to offer a more comprehensive assessment of the relative effectiveness of behavioural strategies.

The cases presented in this paper suggest that the answer to whether "behavioural strategy is coming of age" is mixed. There have been profound strategic decision failures that were at least partly due to cognitive biases that were not debiased and promising successes when debiasing has been applied, which demonstrates that deliberate debiasing can improve the quality of strategic decisions. What is clear from the above cases is that strategic managers need to debias their business decisions. Our success cases provide evidence that debiasing can work, while our failure cases show that not debiasing can be disastrous. Leaving strategic decisions to chance seems both foolhardy and irresponsible. We urge humility as a foundation.

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CHAPTER 3 : HOW ORGANISATIONAL STRUCTURE INFLUENCES UNDERPERFORMING BUSINESS UNITS: RECOVERY, EXIT, AND CORPORATE PROFITABILITY

Kamzabek, T., & Lovallo, D. (2025). How organisational structure influences underperforming business units: Recovery, exit, and corporate profitability. *Working paper*.

HOW ORGANISATIONAL STRUCTURE INFLUENCES UNDERPERFORMING BUSINESS UNITS: RECOVERY, EXIT, AND CORPORATE PROFITABILITY

In 2014, despite nearly a decade of cumulative losses amounting to $7.8 billion in its television division, Sony's CEO Kazuo Hirai firmly declared: "If you are asking if we have any plan to sell off our TV business, I can say we have absolutely no plan to do so right now" (Forbes, 2014). Similarly, in 2020—just a year before LG exited its mobile phone business after 22 straight quarters of losses—CEO Brian Kwon expressed optimism: "Considering the competence of the products and change in line-up that we are preparing, as well as new products that will change the premium landscape, we think we can pull off a turnaround in 2021" (ZDNET, 2020).

Such cases reflect a broader and persistent strategic dilemma: Should firms continue investing in underperforming business units, or divest and reallocate resources elsewhere? This puzzle is far from rare, Elfenbein and Knott (2015) find that nearly half of all business exits occur significantly later than would be considered optimal.

Scholars have long sought to explain this pattern, drawing on multiple theoretical perspectives that emphasize different drivers of firms' decisions to retain or exit struggling units, specifically in multibusiness firms. The following section reviews some prominent theories, shows how they explain persistence or exit, and outlines the approach we take to understand why firms respond differently.

Background and research aim

Background

Whether firms should exit or attempt to recover underperforming units has long been a central question in strategic management (Kolev, 2016). This persistent dilemma has attracted extensive scholarly attention, prompting a range of theoretical explanations. Among the most prominent are three perspectives—*escalation of commitment*, the *behavioural theory of the firm*, and *corporate socialism*—each offers distinct insights into the psychological, organisational, and political dynamics at play. While some of these theories suggest that exit is a rational or necessary response,

others highlight why divestment can be difficult. These perspectives highlight different underlying mechanisms and therefore make differing predictions about whether underperforming units are ultimately recovered or divested.

Escalation of commitment theory. The theory of escalation of commitment attributes the decision to exit or stay to cognitive bias—most notably the sunk cost fallacy, where past investments or losses irrationally influence decision makers to continue allocating resources to failing ventures despite their negative prospects (Sleesman et al., 2018; Staw, 1976, 1981). Research show this bias is pervasive in practice, ranking among the top three most critical managerial blind spots among Forbes Global 2000 managers (Muntwiler et al., 2025).

A key moderator is the availability of alternative business opportunities. Studies show that viable alternatives increase firms' willingness to abandon underperforming units, as continuing investment incurs economic opportunity costs (e.g., Burson et al., 2013; Drummond, 2014; Harvey & Victoravich, 2009; Kolev, 2016; Kwong & Wong, 2014; Lowe & Ziedonis, 2006; McCain, 1986; Northcraft & Neale, 1986). Multi-business firms are particularly less prone to sunk cost fallacy, as they can redirect resources to more promising units, including redeploying nonfinancial (e.g., employee, infrastructure) assets across related markets (Dickler et al., 2022; Feldman & Sakhartov, 2022; Sohl & Folta, 2021b). For instance, studies show that multi-business firms exit declining markets at a rate 11–37% faster than single-business firms due to their internal redeployment capabilities (Dickler & Folta, 2020; Sohl & Folta, 2021b).

Corporate socialism. While the implications of (de)escalation of commitment highlight the psychological mechanisms that can reduce persistence in failing units, particularly when firms operate multiple businesses, other perspectives emphasise structural features of diversified firms that may instead reinforce persistence. In particular, the presence of multiple businesses grants firms access to internal capital markets that can buffer various shocks.[4] The internal markets enable

[4] Williamson (1970, 1975) argued that internal capital markets within multidivisional firms allow for the efficient allocation of resources to high-yield opportunities, as corporate headquarters possesses superior information relative to external investors. This

cross-subsidisation from stronger to weaker divisions, allowing underperforming units to persist despite sustained poor performance (Duchin & Sosyura, 2013; Ozbas & Scharfstein, 2010). Such reallocations, however, are often politically motivated and economically inefficient—commonly referred to as corporate "socialism" (Gopalan et al., 2007; Rajan et al., 2000; Scharfstein & Stein, 2000; recently reviewed by Sengul et al., 2019; Shin & Stulz, 1998).

Empirical studies suggest that internal misallocations are often driven by lobbying pressure and a desire to preserve internal stability (Arrfelt et al., 2013; Cremers et al., 2011; Meyer et al., 1992; Rajan et al., 2000; Scharfstein & Stein, 2000). Evidence indicates that firms reallocate internal funds to weaker divisions in 48% to 75% of cases (e.g., Billett & Mauer, 2015; Vieregger, 2013). Thus, diversification does not necessarily trigger de-escalation of commitments but often serves as a buffer—enabling underperforming units to pursue recovery efforts rather than face immediate divestiture.

Behavioural theory of the firm. This theory reflects managerial bounded rationality—specifically, firms do not maximize profit in the classical economic sense but instead assess performance relative to aspiration levels (Cyert & March, 1963). These aspirations are often hierarchically structured, with survival as the primary goal (e.g., Audia & Greve, 2006), followed by comparisons to sibling units and historical performance (Posen et al., 2018).

According to the behavioural theory of the firm, when a business unit underperforms relative to its aspirations (e.g., survival goal, historical performance, sister units), it triggers a problemistic search aimed at restoring performance and ensuring survival (e.g., Cyert & March, 1963; Posen et al., 2018). In such cases, corporate headquarters typically intensifies oversight (Sengul & Obloj, 2017) and implements remedies, such as cost-cutting or pursuing riskier, resource-intensive actions, depending on the firm's resource availability (Posen et al., 2018). Firms with sufficient resources are more likely to reinvest (Lim & Audia, 2020), often increasing capital

view laid the foundation for later models emphasizing the potential efficiency of internal capital markets (e.g., Myers & Majluf, 1984), though empirical research has increasingly highlighted their political and distortionary aspects (Sengul et al., 2019).

expenditures, launching innovation initiatives, or engaging in explorative searches (Arrfelt et al., 2013; Bromiley, 1991; Greve, 2003; Kuusela et al., 2017; Lu & Wong, 2019; Ma et al., 2023; Zhang et al., 2024). By contrast, divestiture tends to occur when recovery attempts fail or when firms lack the resources necessary to support a turnaround (Audia & Greve, 2006; Kuusela et al., 2017). Thus, firms do not necessarily seek to divest in situations of underperformance; rather, they may pursue resource-intensive investments, particularly when sibling units can provide internal support.

Research aim

We draw on three prominent theories to highlight competing explanations for how firms respond to underperforming business units. Specifically, the predictions of escalation of commitment stand in contrast to those of corporate socialism and the behavioural theory of the firm.

Our study seeks to explain why firms' responses diverge, not by challenging the underlying mechanisms (e.g., cognitive biases, agency issues, or aspiration-level comparisons), but by showing that their effects are contingent on *corporate partitioning*. Specifically, *corporate partitioning*, how a firm defines and separates its business units, is a factor that shapes whether the firm is more likely to recover or divest underperforming segments. Because partitioning plays a role in both the relative power of business units and their access to internal resources, it is critical to how firms respond to persistent underperformance.

We organise the remainder of the study as follows. In the next section, we develop our hypotheses by introducing the concept of corporate partitioning and explaining how it shapes resource allocation to underperforming business units and influences subsequent corporate outcomes. We then present our methodology, followed by the empirical results in Section 3. In the discussion section, we interpret our findings and return to the three theoretical perspectives (escalation of commitment, corporate socialism, and the behavioural theory of the firm), to clarify how our results contribute to, and extend, these distinct viewpoints.

Hypothesis development

Firms do not evaluate underperforming units in isolation; we argue that decisions to retain or divest these units are shaped not only by performance thresholds or external pressures, but also by how corporate operation is structurally organised. Specifically, *organisational partitioning*, the way business units are grouped and separated, affects internal power dynamics (Bardolet et al., 2017; Pfeffer & Salancik, 1974), managerial cognition (Bardolet et al., 2011; Burson et al., 2013; Kwong & Wong, 2014) and access to resources (Sengul et al., 2019; Williamson, 1970, 1975), shaping whether a struggling unit is seen as strategic or expendable. We introduce *corporate partitioning* as a key mechanism for resolving the dilemma of whether firms should exit or retain underperforming units, as it affects how managers interpret performance shortfalls and their willingness to allocate internal resources. In the following section, we first outline the different types of partitioning before examining how these partitioning choices shape firms' responses to underperformance.

Organizational partitioning

In this section, we discuss corporate partitioning, its various forms, and its implications for recovery and exit decisions. Regardless of size, firms vary in how they partition their diversified operations. Some firms adopt coarse partitioning, grouping businesses into a few broad divisions/segments/groups, whereas others employ finer partitioning, dividing operations into a larger number of smaller, more focused units (Argyres & Lovallo, 2024; Sengul & Yu, 2024) (see Table 3-1). In the consumer goods industry, for instance, Unilever (prior to 2022) combined beauty and personal care into one division, whereas Procter & Gamble separated its units (Lafley & Martin, 2013; Sengul & Yu, 2024). These structural differences often reflect organisational preferences and strategic priorities. Managers seeking to leverage economies of scope across shared technologies, customer bases, or infrastructure frequently favour coarse structures (Blau, 1970; Dewar & Hage, 1978; Sengul & Yu, 2024; Simon, 1947; Zhou, 2013). Conversely, those prioritising accountability, transparency, or innovation may adopt finer partitioning to enhance

visibility into unit-level performance and facilitate exploration (Argyres & Lovallo, 2024; Christensen & Raynor, 2013; Guadalupe & Wulf, 2010; Rajan & Wulf, 2006).

Table 3-1 Types of Partitioning and Their Implications for Recovery and Exit Decisions

Structural Form	Unit's Power	Access to Internal Resource Market	Implications for Recovery / Exit
Coarse partitioning	High	Low • Loss in one unit significantly affects overall firm performance. • Few opportunities for internal coinsurance (i.e., offsetting losses in one division with gains in another).	• The unit's power motivates the firm's choice to pursue recovery. • Limited internal resources constrain recovery efforts.
Moderate partitioning	High	High • A larger number of units enables internal resource pooling and cross-subsidisation.	• The unit's power motivates the firm's choice to pursue recovery. • Sufficient internal resources support effective turnaround strategies.
Finer partitioning	Low	Low • "Winner-picking" logic dominates resource allocation: Resources are concentrated on high-performing units.	• Recovery is deprioritised. Underperforming units are more likely to be viewed as expendable and exited.

Coarse partitioning

When a firm adopts a coarser organisational structure—operating with a few large divisions—each unit typically has substantial influence within the organisation. In such settings, segments hold greater *power*. Burson et al. (2013)'s experiment shows that when individuals manage fewer units, decision makers are more inclined to ask, "Why should we retain this unit?" rather than, "Why should we divest it?" a framing that activates psychological biases toward retention. Each unit is more likely to be perceived as unique and indispensable (Kogut & Ritov, 2005; Small et al., 2013). Burson et al. (2013) also aligns with loss aversion theory, in coarse structures, each division is cognitively framed as an irreplaceable part of the firm, making its divestiture feel like a salient loss rather than a marginal adjustment, thereby triggering greater resistance to exit. This valuation, in turn, increases such units' power to attract internal resources (e.g., Pfeffer & Salancik, 1974). Their relative size and visibility further enhance their influence over resource allocation and strategic decisions (Bardolet et al., 2017; Keum, 2023; Kim et al., 2004; Pfeffer & Salancik, 1974; Watson & Wooldridge, 2005). By virtue of their contribution to overall firm performance, coarser

units can exert disproportionate pressure to preserve their existence and secure continued support—even when underperformance might otherwise justify divestment.[5]

However, the feasibility of recovery ultimately depends on the unit's *access to resources*. In firms with very coarse structures (i.e., only two divisions), internal capital reallocation is inherently constrained (despite a unit's *power*) because losses in any single division tend to be large relative to the firm's total resources. For example, Hoang et al. (2024) demonstrate that firms with fewer business lines are less likely to engage in cross-subsidisation to support underperforming units. They note that this is partly because performance across divisions tends to be more correlated—when one division underperforms, the entire firm is typically affected. As a result, the potential for internal coinsurance (i.e., offsetting losses in one division with gains in another) is significantly reduced (Hoang et al., 2024), often leaving divestments as the only viable option (Duhaime & Baird, 1987; Kuusela et al., 2017). A classic example is Sears Holdings, where persistent underperformance at Kmart drew financial support from its sibling, Sears. However, the firm's extremely coarse, two-segment structure limited the scope for internal reallocation, ultimately failing to restore Kmart's performance and contributing to a broader systemic decline and eventual bankruptcy.

However, as the number of segments increases, access to internal resources also improves, since more high-performing divisions can absorb losses and support turnaround efforts (Hoang et al., 2024). For example, Morandi Stagni et al. (2021) suggest that more diversified firms are more likely to continue exploratory investments in a segment during periods of heightened pressure and shocks. Similarly, Gopalan et al. (2007) find that Indian business groups with multiple siblings

[5] Additionally, underperformance can be interpreted not as a localized issue, but as a broader organizational concern, prompting headquarters to favour recovery over exit. For example, Joseph and Ocasio (2012) document GE's experience of its Medical Systems lagging in CT scanner adoption in the early 1970s. During the preceding corporate planning era (1963–1971), GE focused on finer partitioning, expanding the number of groups, divisions, and departments and creating more semi-autonomous units. However, from the early 1970s GE's strategic planning reforms shifted its focus toward a relatively coarser partitioning: sector and group structures were created, corporate HQ integrated strategic, operational, and financial oversight, and cross-level channels were established to link corporate executives with business units. As Medical Systems operated as a major business unit within this coarser architecture, corporate headquarters directly pressured its leadership to prioritize CT development, and redirected resources from Corporate R&D—a centralized innovation hub serving multiple segments—to fund a crash development program. This decision allowed GE to restore competitiveness without medical systems bearing the full cost or risk.

recognise the negative spillover risks associated with the failure of one unit, and are therefore incentivised to intervene. They show that business groups embedded within internal resource markets face a 34.5% lower probability of bankruptcy compared to standalone businesses (see also Cestone & Fumagalli, 2005). Leveraging this internal safety net, underperforming units in such firms often benefit from increased capital expenditures and overhead investment as part of their recovery plans (see Ma et al., 2023). As a result, up to a certain level of partitioning, firms remain motivated (due to a unit's *power*) and better positioned (due *to internal resource availability*) to retain and recover underperforming divisions.

Finer partitioning

In contrast, in firms with a large number of finely partitioned business units, any single unit tends to hold less *power* within the overall corporate portfolio due to both limited managerial bandwidth and stronger incentive alignment. Executives in finely partitioned firms may lack the bandwidth to fully understand each unit's performance drivers and turnaround potential (Christen et al., 2009). This arises because the cognitive load on top managers increases disproportionately with each additional unit, as decision makers must monitor, interpret, and compare performance signals across more contexts, each with distinct sources of uncertainty (Christen et al., 2009). Moreover, because managerial data processing capacity is fixed or expands only slowly, the marginal attention devoted to each unit declines as the number of units grows, resulting in noisier assessments and greater reliance on simple heuristics (Christen et al., 2009). As a result, executives may adopt more straightforward "winner-picking" approach (e.g., Maksimovic & Phillips, 2002; Stein, 1997), allocating resources to high-performing units while treating underperformers as expendable. This approach limits struggling units' access to *internal resources* and reduces the likelihood of organisational support for recovery.

Morrin et al. (2012), for instance, show that when individuals are presented with more units (e.g., 15–25 funds), they tend to focus on a small subset, choosing only 3.68 to 6.22 on

average. Applied to firms, such partitioning can facilitate the de-escalation of commitment by increasing the salience of opportunity costs (Klingebiel & Rammer, 2021; Northcraft & Neale, 1986), in turn reducing psychological exit barriers (Burson et al., 2013; Kwong & Wong, 2014; McCain, 1986). Related to this, other authors (Bernard & Jensen, 2007; Colombo & Delmastro, 2001; Lieberman, 1990) find that multiplant firms are more likely to close individual plants. This tendency is particularly pronounced when plants differ significantly in their cost structures, as such internal dissimilarity enables firms to more easily identify and disengage from poorly performing plants (Bernard & Jensen, 2007).

At the same time, finer partitioning narrows the scope of activity within each unit, making individual units more transparent and accountable, which enables clearer performance tracking and stronger incentive alignment (Argyres & Lovallo, 2024; Guadalupe & Wulf, 2010; Rajan & Wulf, 2006). Scholars (Guadalupe & Wulf, 2010; Rajan & Wulf, 2006; Wulf, 2012) document a trend toward flatter hierarchies, this structural change often coincide with compensation reforms, tying division managers' incentives more closely to both unit and firm-level performance, enabling firms to better respond to external competition. Wulf (2012) also showed that CEOs flatten their organisations not to decentralise, but to increase their own strategic control and speed of response, often by reducing intermediaries.[6] Doing so reduces the likelihood of weak divisions "hiding" within aggregated structures (Baghai et al., 2009), thereby encouraging a shift from isolated evaluation to comparative assessment. As a result, finer partitioning might be less vulnerable to lobbying by lower-level managers and are more structurally equipped to reallocate resources away from persistently weak units (Argyres & Lovallo, 2024).

Therefore, putting these framings together: when partitioning is relatively coarse, business units tend to be relatively large and powerful (because top management places greater value on

[6] Firms can also use internal ranking systems to evaluate unit performance under finer partitioning. Knott and Turner (2019) demonstrate that such partitioning enhances innovation by fostering a dynamic cycle of imitation and innovation—where underperforming units strive to catch up by imitating top performers, and leading units continue to innovate in response to this pressure. This process may facilitate performance heterogeneity and increases the visibility of underperforming units, enabling firms to more effectively target them for recovery or divestment.

these units and their relative size affords greater lobbying influence within the organisation). In such settings, underperforming units are more likely to be protected or cross-subsidised by better-performing peer(s), especially when singling segments absorb temporary losses. This structural configuration supports recovery-oriented responses, as firms are more willing to commit resources to turn around weak units. As partitioning increases to a moderate level, the presence of more "siblings" can enhance internal resource inflow, and underperformance may still be tolerated, given that other units can provide financial support and managerial attention remains relatively concentrated. However, beyond a certain threshold (what we refer to as finer partitioning), individual units become smaller and carry less power. At this point, even though other units may still be able to provide support, the firm becomes more inclined to deprioritise or divest underperforming segments. This shift reflects a structural transition from escalation of commitment to comparative evaluation and accountability, where weak units are more easily identified and less able to justify continued investment.

H1: The relationship between the number of business segments and the likelihood of recovery efforts follows an inverted U-shape, holding firm size and other factors constant.

H2: The relationship between the number of business segments and the likelihood of exit follows a U-shaped pattern, holding firm size and other factors constant.

Implications for overall corporate performance

This section explores the implications of organisational partitioning for corporate performance, specifically aiming to develop hypotheses regarding whether firms should pursue recovery or exit strategies given their structural configuration.

Organisational partitioning not only influences how firms respond to underperforming business units but also shapes the broader performance consequences of those responses. Because partitioning affects how resources are distributed within the firm, it determines the costs and benefits associated with recovery or exit decisions at the corporate level. In other words, it is the

alignment—or misalignment—between organisational structure and strategic response (whether to recover or divest) that ultimately drives whether these actions enhance or undermine overall firm performance (see Table 3-2).

Table 3-2 Implications for Partitioning Types for Corporate Performance

Structural Form	**Spillover Effect of Termination**	**Cost of Termination ("Next-Best Use" for Physical/Non-Scale-Free Assets).**	**Implications for Firm Performance**
Coarse partitioning	High	High • Units are too large and deeply embedded • Difficult to sell • Difficult to repurpose	Recovery is favoured • Exit is costly due to high redeployment barriers and potential reputational spillovers. • Firms may benefit from pursuing recovery strategies, particularly when underperforming subunits/projects are hidden within an aggregated portfolio. In such cases, adopting a more granular view—or revisiting the firm's partitioning structure—can enable more targeted interventions.
Finer partitioning	Low	Low • Can be sold externally • Easier to repurpose	Exit is favoured • Firms can reallocate resources to better-performing units. • Exit is low-cost and generates minimal spillovers.

In firms with coarsely defined divisions, the failure of a single unit can have disproportionately large *spillover* effects on corporate outcomes. Such failures can be consequential due to the unit's central role in shaping the firm's identity (Burson et al., 2013) and the visibility of its contribution to overall performance (Clinebell & Clinebell, 1994; Gopalan et al., 2007; Zuckerman, 2000). Terminating even one business unit in a firm with only a few segments can raise concerns about its stability and long-term prospects, potentially damaging the firm's reputation (Duhaime & Baird, 1987; Gopalan et al., 2007; Varadarajan et al., 2006).

Research suggests that divestitures of large, visible units often occur only after multiple failed recovery attempts and significant firm-level decline. For example, Duhaime and Baird (1987) based on interviews with large U.S. firms (including many from the Fortune 500), show that such exits are typically a lagging indicator of broader organisational decline, rather than a pre-emptive corrective action. Similarly, Gopalan et al. (2007) find that the failure of a single group in an Indian business family caused reputational damage that reduced access to external capital by 21% and cut

profitability across sibling businesses by 32%. These findings highlight how termination decisions can produce negative spillovers beyond the focal unit.

Beyond reputational *spillovers*, *termination costs* can significantly undermine subsequent profitability, as the financial burden of exit reduces overall corporate performance. Specifically, coarse units often consist of tightly bundled, immobile resource configurations that are difficult to decouple and redeploy elsewhere in the organisation (e.g., Helfat & Eisenhardt, 2004; Khanna et al., 2018). When such units are operationally distant from their siblings, firms may struggle either to repurpose assets (e.g., employees, plants, etc) internally due to their scale or to find external buyers, as it may be costly for other firms to integrate these assets into their existing operations or restructure them for alternative uses (Helfat & Eisenhardt, 2004; Karim, 2006; Sakhartov & Folta, 2014; Sakhartov & Folta, 2015). These costs are especially pronounced when divisions are highly specialised, unrelated to other businesses, or involve substantial sunk investments (Levinthal & Wu, 2024; Morandi Stagni et al., 2020). Although firms may attempt to restructure or disaggregate such unit (i.e., coarse) to make them more marketable (Karim, 2006), or terminate select technologies, Khanna et al. (2018) suggests that this process is often delayed due to cognitive complexity of disentangling interrelated technologies. As a result, terminating operations within coarse units is typically more costly and prone to negative spillover effects, making retention, restructuring, or attempted recovery relatively more attractive.

For example, Unilever had long faced sluggish growth in its Foods & Refreshment division, which became increasingly difficult to manage alongside unrelated Beauty & Personal Care and Home Care segments. Given both structural distance, the company initiated a major reorganisation in 2022, restructuring into five business groups and dividing Foods into two to enable greater focus and accountability, while also actively divesting underperforming food businesses (*Financial Times*, 2025; Unilever, 2022). This move reflects the broader logic that firms with coarse structures may benefit from recovery strategies such as adopting a more granular portfolio view or separating units, thereby enabling clearer performance attribution and more

flexible resource allocation (Argyres & Lovallo, 2024; Baghai et al., 2009; Guadalupe & Wulf, 2010).

In contrast, under finer partitioning, the failure of an individual unit generates weaker negative *spillovers* across the organisation, as each unit is more loosely coupled with the firm's overall identity and performance (Bergh, 1995; Gombola & Tsetsekos, 1992; Hoang et al., 2024). As a result, such structures can facilitate more rapid exits from failing initiatives and support more selective investment strategies. Although Vidal and Mitchell (2015, 2018) and Klingebiel and Rammer (2021) do not directly examine partitioning structures, their findings suggest that firms often pursue proactive divestments as a strategic mechanism to reallocate resources toward more promising opportunities. Importantly, such resource reallocation is associated with superior innovation outcomes (Klingebiel & Rammer, 2021).

For instance, the closure of LG Electronics' mobile business, representing roughly 6% of corporate revenue, was followed by a 48.4% increase in overall revenue of LG and a 65.5% rise in operating profit in the second quarter of 2021 compared to the same period the previous year (Strata-gee, 2021). Moreover, in parallel, LG reassigned employees from the discontinued mobile division to other electronics units, highlighting an effective internal redeployment of capital (Businesskorea, 2021). Such divestitures facilitate the reallocation of both physical and human assets, commonly referred to as "non–scale-free" resources, to their next-best use, thereby reducing the cost of termination (Levinthal & Wu, 2024). Supporting this perspective, prior research shows that firms with a greater number of related and modular business units are structurally better positioned not only to reconfigure and redeploy resources internally, but also to divest assets through external markets (Helfat & Eisenhardt, 2004; Karim, 2006; Sakhartov & Folta, 2014; Sohl & Folta, 2021a, 2021b). While we do not directly measure modularity, we argue that finer partitioning, by organising business units around narrower sets of resources, tends to produce more modular structures than coarse partitioning. This relative modularity limits interdependencies across units, thereby enabling firms to reconfigure resource bundles, redeploy

personnel, or divest underperforming segments with lower coordination and transaction costs, ultimately reducing the financial burden of termination.

Taken together, these patterns suggest that the performance value of recovery versus exit is contingent on how finely the firm is partitioned. We hypothesise:

H3: In firms with a coarser structure, exiting an underperforming unit is associated with inferior corporate performance compared to retaining or recovering the unit, holding other factors constant. In contrast, in firms with a finer structure, exit leads to superior corporate performance relative to recovery efforts, all else being equal.

Methodology

Sample

We used a sample of S&P 1500 companies from COMPUSTAT. We excluded public administration firms (SIC 9100–9999), financial firms (SIC 6000–6999), and utility firms (SIC 4900–4999) due to their differing performance measures and regulations (e.g., Hu et al., 2023). To ensure meaningful analysis of corporate partitioning, we included only firms with at least two operating business segments.[7]

Our level of analysis is the business segment, with COMPUSTAT classifying segments based on a company's reported industry segments or product lines. A notable limitation of the segment data is the variability in the criteria different firms use to define a business segment or unit. Additionally, some firms report multiple business segments within the same industry (SIC 4 digits), complicating the identification of a specific segment involved in asset sales or exits. These business segments are also inconsistently named across different periods. To effectively manage these complexities, we adopted the consolidation technique, grouping reported segments at the four-digit SIC code level as a single business segment (e.g., Biddle et al., 2024; Dickler et al., 2022; Lamont, 1997; Morandi Stagni et al., 2020; Ozbas & Scharfstein, 2010; Wang, 2023). This method allows for a more standardised comparison of business segments. We also dropped the segments with negative and zero sales and assets.

We focused on loss-making business segments, particularly those exhibiting sustained downturns or inconsistent profitability. The sampling criteria were designed to ensure that our analysis targeted units facing genuine performance challenges rather than occasional fluctuations. The sampling criteria are as follows. *First*, from our initial sample of all business segments within firms between 2000 and 2018, we selected those that had experienced negative profitability. *Second*,

[7] We observe that some firms change their partitioning over time, either reducing to a single business or expanding substantially. Therefore, we focused on firms that had at least two segments for most of the observation period.

we excluded businesses' initial profitable periods, including only periods of negative profitability in the first year (see Table 3-3). This decision reflects our assumption that underperformance begins with the initial loss-making year, and we aim to track the timing and trajectory of recovery or exit from that point forward. For instance, in the example in Table 3-3, we dropped Y1 and Y2 due to positive profitability in these periods, commencing our analysis from Y3 as first observation, when the segment became unprofitable. *Third*, we also excluded periods where the business had constant profitability. For example, Y11 and Y12 were excluded because they demonstrated sustained profitability following profitable Y10.[8] Using survival analysis, we aimed to estimate the duration required for a segment to return to a stable, profit-generating state following the onset of underperformance. Including such profitable periods would artificially extend the estimated time to recovery, as it would incorporate years not reflective of underperformance, thereby distorting the timing and nature of the recovery trajectory. *Fourth*, some businesses demonstrated irregular patterns—experiencing long profitable years after an initial loss, only to register an isolated unprofitable year, before returning to profitability. For instance, we dropped segments where a segment was unprofitable in its initial year, then profitable for five consecutive years, followed by one isolated loss in year six, and then a return to profitability. These segments were not deemed as underperforming, as their rare losses did not reflect a visible downturn. To address this, we concentrated on businesses exhibiting performance volatility (i.e., unprofitable for at least 50% of the time) or clear underperformance (e.g., consistent losses over two years or multiple times). This step ensured that we excluded statistical noise, segments with isolated losses amid an otherwise strong trajectory, that could confound the interpretation of recovery or exit behaviour. This approach allowed us to focus on business segments characterised by uncertainty and fluctuating performance, where the prospect of future profitability was less predictable.

[8] We retained profitability periods that occurred between negative periods, such as Y6 and Y8, as the firm did not exhibit signs of consistent profitability.

Table 3-3 Sampling Example

Year	Y1	Y2	Y3	Y4	Y6	Y7	Y8	Y9	Y10	Y11	Y12
Profitability of segment	+	+	–	–	+	–	+	–	+	+	+
Included in our sample?	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Time in Analysis (year)			1st	2nd	3rd	4th	5th	6th	7th		

We ran survival analysis (Cox, 1972; Gutierrez, 2002; Prentice et al., 1981) to estimate the duration of a business until an event occurred, starting from when a business began to be unprofitable. To address the issue of left-censored data, we excluded all businesses with initial observations beginning (i.e., segment that were unprofitable) in 2000 because underperformance for these businesses may have commenced before 2000. Thus, we confirmed that all included businesses were profitable at the start of 2000, with any unprofitable periods occurring only after this date. Our final sample consists of 5,306 observations.

Dependent variables

Segment recovery. As survival model requires the dependent variable to be a binary, we assigned a value of 0 to periods when the business was unprofitable, and 1 to periods of profit. In our final sample 1,372 businesses exited loss-making segments.

Segment exit. We examined two distinct types of exit strategies: (1) business shutdown and (2) asset sale.

Business shutdown was classified as a business discontinuing reporting in the following year and failing to generate a profit in the final year of observation. In our final sample, 735 businesses were shutdown. This variable is significantly associated with a reduction in corporate-level asset size (see Appendix, Table 3-A1) and is negatively related to earnings from discontinued operations (see Appendix, Table 3-A2), supporting our interpretation of discontinued reporting as an indicator of shutdown.[9]

[9] As reported in Appendix, Table 3-A1, firms that discontinued underperforming segments experienced, on average, a 5% decline in total assets ($\beta = -0.05$; $p < 0.01$), after accounting for segment and firm size, M&A activity, and asset sale earnings. This finding underscores the material impact of segment withdrawal on corporate scope. Complementing this result, Appendix, Table 3-A2 shows that discontinued reporting is negatively associated with divestment-related earnings ($\beta = -0.005$; $p < 0.01$), suggesting that such exits are more likely to reflect terminations or write-offs rather than earning from asset sales. Taken together, these patterns indicate that discontinuation often entails business shutdowns.

Asset sale involved capturing cases where firms divested underperforming assets through external markets. We used the SDC Platinum dataset, which records corporate asset divestitures. We assigned a value of 1 if assets within the underperforming business segment were sold to another firm, and 0 otherwise. Our final sample includes 163 such asset sale events.

Firm performance was measured using industry-adjusted ROA (Pavićević & Keil, 2024; Zhang, 2006) in a subsequent year and over a three-year horizon (mean of year t, t+1, and t+2).

Independent variable

Number (N) of sibling segments. We counted the businesses operated by the firm as an alternative to our focal business segment. Specifically, we aggregated reported segments at the four-digit SIC code industry level and counted the total number of segments (excluding focal segment).

Design and endogeneity

Part 1. To estimate the likelihood of shutdown, sale, and recovery events, we employed survival analysis. Our dataset has two key features: (1) recovery and asset sale events can recur multiple times, unlike one-time exit events. For example, as shown in Table 3-3, recovery is observed in both Y6 and Y8 (two recoveries over a seven-year observation window). Similarly, firms may sell segments assets (i.e., subunits, plants, etc.) incrementally over several years, making asset sales a repeated process. (2) covariate effects vary across years and events. To account for these dynamics, we applied the Prentice, Williams, and Peterson Total Time (PWP) model (Prentice et al., 1981), an extension of the Cox proportional hazards model designed for recurrent events. The model employs a stratified proportional hazard approach, stratifying the analysis by the sequence of event occurrences. It operates under the premise that a business is not exposed to a subsequent event (e.g., recovery or asset sale) occurrence until the preceding one has taken place. That is, instead of using the classical Cox method that resets the time to zero after each event for a given business, this method allows the time measure to continually increase after each event for

a given business segment (Lee & Wang, 2003; Prentice et al., 1981). The time to an event is always measured from the start of the data collection (i.e., 1st observation) for that unit whereas the Cox model accounts for longitudinal data, adjusts for covariates that may change with time, and accommodates right-censoring data (Cox, 1972). In addition, we included industry and year fixed effects to account for unobserved heterogeneity across industries and time periods.

To address concerns about endogeneity arising from omitted variable bias (Hill et al., 2021), where unobserved factors may simultaneously influence both the independent and dependent variables, we employ shared frailty models. These models are particularly well-suited for unobserved, time-invariant heterogeneity at the industry, firm, or segment level (Gutierrez, 2002). By including a frailty term, the model assumes that business segments within the same group (e.g., firm, industry, or segment type) share latent characteristics that systematically affect the hazard rate (details in Cleves, 2008).[10] This approach has become increasingly common in strategic management research (e.g., Bigelow et al., 2019; Kim, 2016; Leone & Reichstein, 2012; Yu et al., 2022). To further address the risk of time-varying omitted variable bias, we conducted robustness of inference to replacement (RIR) tests (Busenbark et al., 2022), estimating a logit model as an alternative specification (Wang et al., 2023). The RIR results indicated that, for our main findings to be overturned by unobserved confounders, these would need to affect at least 40% of the recovery sample, 32% of the shutdown sample, and 42% of the asset sale sample with a bias strong enough to fully explain the observed effects. This analysis strengthens our confidence that omitted variable bias is unlikely to substantially affect our conclusions.

Part 2. Since survival analysis is not suitable for estimating corporate performance, we used a dynamic panel model with system generalised method of moments (GMM) estimation (Arellano & Bond, 1991; Roodman, 2009). This modelling approach is well-suited to our empirical setting for two main reasons: first, it addresses the autocorrelation in ROA, where past performance

[10] The main limitation of the frailty model is that it does not account for performance persistence. To address this, we also include lagged *recovery* status to capture state dependence in performance outcomes, isolating the effect of new recovery events from ongoing improvements. This complements the frailty specification, which accounts for unobserved heterogeneity.

significantly influences current outcomes; Second, it addresses the potential endogeneity of both the N and ROA, which may be shaped by unobserved firm-level characteristics or by strategic decisions made in earlier periods.

The GMM procedure addresses these concerns in two steps. First, the first-differencing transformation removes unobserved, time-invariant characteristics by subtracting the previous year's value of each variable (i.e., ROA, N, and control variables) from the current year's value. This helps eliminate firm-level fixed effects that could bias the estimates. Second, the estimator uses lagged values of the explanatory variables as instruments, correcting for potential simultaneity and reverse causality (Wintoki et al., 2012)—such as the possibility that firms with stronger current or expected performance may be more likely to diversify, increasing N. Together, these features allow us to obtain more consistent and unbiased estimates of the relationship between corporate partitioning structures and firm performance over time.[11] This approach has also been adopted in recent research on diversification and organisational structure (e.g., Alessandri & Seth, 2014; Cadot et al., 2011; Girod & Whittington, 2017; Hashai et al., 2025).

Control variables

To isolate the effect of corporate partitioning as a strategic preference rather than a structural necessity, we include several control variables at both the firm and segment levels. First, we control for *firm size*, measured as the logarithm of total corporate assets, based on the premise that partitioning reflects managerial choice rather than a constraint imposed by firm scale. Because segment sizes vary, with some units significantly larger than others, we also control for the *relative size* of the focal segment, calculated as its share of total firm assets. To control for business unit attractiveness, we include business *segment-level growth*, which may incentivise retention even when current profitability is low (Wennberg et al., 2016). Additionally, following escalation of

[11] Wintoki et al. (2012) emphasize that this method is particularly suitable when the key variables—such as N and ROA—are highly persistent over time (i.e., strongly correlated with their own lags), a situation in which traditional fixed effects models may yield biased or inconsistent results.

commitment logic (Staw, 1976, 1981), we control for *sunk costs*, measured as cumulative losses since the start of observation, normalised by firm sales.

To account for internal resource availability, we include lagged firm's *operating cash flow*, which captures the performance of sibling units, and *equity-to-debt* ratio, reflecting the firm's obligations, resource constraints, or slack (Kuusela et al., 2017).[12] We also control for *relatedness* among business units, which lowers redeployment costs and supports recovery decisions (Lieberman et al., 2017; Sakhartov & Folta, 2014). This is measured as the ratio of assets in sibling units that share the same two-digit SIC code to total firm assets. A higher ratio indicates greater potential for internal asset redeployment or relocation. Finally, to capture industry-level structural constraints, we include a measure of *industry coarseness*, proxied by the logarithm of the average firm size within the industry. Larger average business size implies broader natural partitioning, which may limit firms' ability to finely structure their segments.

[12] By controlling for corporate performance, we account for the possibility that sibling segments were also underperforming, an internal condition that could significantly reduce the likelihood of recovery for the focal segment due to constrained resources.

Results

Partitioning and recovery

Table 3-4 presents descriptive statistics for all variables used in the analysis, while the Appendix, Table 3-A3 displays the correlation matrix. To test H1, which proposes an inverse U-shaped relationship between the level of partitioning and the likelihood of recovery, we begin by estimating the hazard of returning to profitability, reported in Table 3-5.

Table 3-4 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Recovery	.258	.438	0	1
Shutdown	.139	.346	0	1
Asset sale	.041	.198	0	1
N	2.009	1.299	0	9
N^2	5.726	8.215	0	81
Firm size	7.389	2.036	2.152	13.137
Segment size	.303	.291	.002	1
Segment growth $^{\omega}$	.283	1.334	-.855	10.021
Sunk cost $^{\omega}$	.066	.179	0	1.476
Equity to debt $^{\omega}$	1.178	1.461	-.364	8.022
Industry coarseness	7.095	1.515	-2.189	10.823
Ind. Adjusted ROA $_{t+1}$ $^{\omega}$	.012	.14	-.444	.552
Ind. Adjusted ROA $_{3\ years}$ $^{\omega}$	.013	.159	-.638	.586

$^{\omega}$ winsorized at 1 and 99 percentiles

Model 1 indicates that the linear effect of the number of sibling segments (N) is not significantly related to the hazard rate of recovery, suggesting that greater partitioning into more segments (holding firm size constant) does not linearly predict the likelihood of recovery. However, Model 2 reveals a nonlinear relationship.[13] Specifically, the inclusion of N ($\beta = 0.123$, $p < 0.05$) and N^2 ($\beta = -0.0186, p < 0.05$) significantly affects the likelihood of profitability (Model 2), confirming a non-linear relationship. A formal U-shaped test (Lind & Mehlum, 2010) confirms this pattern at the 5% significance level, with the turning point estimated at 3.33 sibling segments—suggesting that profitability is maximised when firms operate with approximately four to five business segments.

[13] Models 1 and 2 showed nearly identical Akaike Information Criterion (AIC) values (17,409.6 vs. 17,409.4), suggesting no improvement in explanatory power from the U-shaped specification (see Table 3-5). However, after accounting for heterogeneity via the frailty term, the non-linear model demonstrated better fit, with a lower AIC (AIC = 2,421.1 vs. 2,423.4).

Specifically, the PWP analysis, which estimates the hazard rate of recovery relative to a baseline of business units with only one sibling, indicates that adding one sibling increases the likelihood of recovery by 7.0%, while two siblings, corresponding to the estimated inflection point, increases it by 9.72%, holding firm's size and other covariates constant. This supports our hypothesis that recovery likelihood peaks at moderate levels of partitioning. In coarsely structured firms with only a few large units, underperforming divisions are often protected and cross-subsidised due to their power. As partitioning increases, we show that additional sibling segments enhance internal resource sharing, thereby improving recovery prospects of underperformers. Notably, the majority of firms (87.9%) fall below the estimated inflection point (see Figure 3-1).

However, beyond a certain threshold, specifically, more than four to five segments, this effect reverses. For example, firms with six segments (roughly mean plus two standard deviations) are 5% less likely to recover a struggling unit compared to those at the moderate level. In rare cases, such as firms reporting eight segments (only 31 observations), the likelihood of recovery declines by as much as 25%. This decline reflects how finer partitioning creates smaller, less powerful units that struggle to attract internal support, reinforcing the firm's tendency to deprioritise underperformers (Argyres & Lovallo, 2024; Maksimovic & Phillips, 2002; Stein, 1997).

These results align with the shared frailty model (Model 3), which accounts for unobserved firm-level heterogeneity and estimates the peak recovery likelihood at 3.3 sibling segments (closely matching the estimate from the PWP model). At this level of partitioning, the expected median time to recovery is approximately 3.47 years—0.28 years (about 3.4 months) faster than in firms with only two segments, and 1.76 years (roughly 21.1 months) faster than in firms with ten segments, all else being equal (see Figure 3-1).[14] Taken together, these findings provide strong empirical support for H1.

[14] The significant N (β= 0.174; p<0.05) and N squared (β = −0.0253; p<0.05) suggest a U-shaped pattern after accounting for unobservable heterogeneity across firms (Model 3). Here, we obtained a significant Ln(theta) coefficient of –2.046 (p < 0.01), suggesting the presence of endogenous heterogeneity across units, indicating that a frailty term is appropriate for capturing unobserved firm-level differences. However, since the exponential value of theta ($e^{-2.046}$≈0.129) is close to zero, the level of

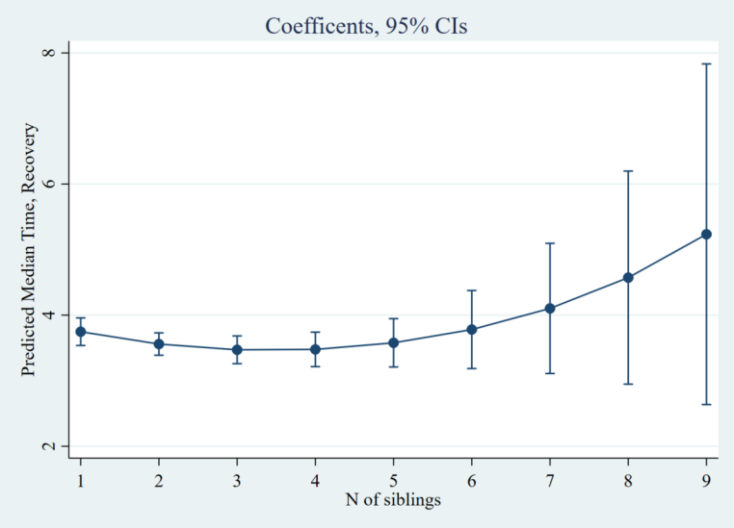

Figure 3-1 Estimated recovery time

N of siblings [15]	1	2	3	4	5	6	7	8	9
Observations	2,217 (41.43%)	1,628 (30.43%)	737 (13.77%)	339 (6.34%)	197 (3.68%)	59 (1.1%)	31 (0.58%)	15 (0.28%)	4 (0.07%)

Partitioning and exit (shutdown and asset sale)

To test our second hypothesis, we examine how the number of sibling units influences the likelihood of exit—specifically, through *shutdowns* and *asset sales* of underperforming units. H2 posits a U-shaped relationship between the N and the likelihood of segment exit.

Models 5 and 6 (in Table 3-5) estimate the likelihood of unit shutdown using PWP and segment-shared frailty models. Both reveal a statistically significant U-shaped relationship. However, the frailty model is preferred due to the significantly positive ln(θ) (β =1.480; p<0.01), which indicates the presence of unobserved heterogeneity in shutdown decisions and suggests the frailty specification is more appropriate (Model 6). The signs of the coefficients—N (β = –0.329, p < 0.01) and N^2 (β = 0.0479, p < 0.01)—reflect a U-shaped effect, with a threshold at three sibling units.

Specifically, we found that, compared to units with only one sibling, having two and three (inflection point) segments reduces the likelihood of shutdown by 18.6% and 27.6%, respectively,

unobserved heterogeneity across firms is relatively small. Thus, these results indicate that the coefficients in the frailty model align closely with those in the PWP model, reinforcing the consistency and robustness of our findings.

[15] In a small number of cases (124 observations, or 2.32%), we observe firms with only a single core segment. This reflects the dynamic nature of corporate partitioning, as firms may occasionally consolidate their structure over time. In these instances, firms temporarily appear as single-segment entities but soon return to a multi-segment configuration.

Table 3-5 Estimates for Recovery, Shutdown and Asset Sale

VARIABLES	(1) Recovery PWP	(2) Recovery PWP	(3) Recovery Frailty	(4) Shutdown PWP	(5) Shutdown PWP	(6) Shutdown Frailty	(7) Asset sale Frailty	(8) Asset sale Frailty
N	0.009	0.123**	0.174**	-0.037	-0.232**	-0.329***	0.193***	0.137
	(0.021)	(0.059)	(0.078)	(0.037)	(0.091)	(0.126)	(0.073)	(0.203)
N^2		-0.018**	-0.025**		0.032**	0.047***		0.011
		(0.009)	(0.012)		(0.013)	(0.018)		(0.026)
Firm size	0.037***	0.037***	0.032*	-0.133***	-0.134***	-0.208***	0.221***	0.227***
	(0.014)	(0.014)	(0.019)	(0.024)	(0.024)	(0.034)	(0.062)	(0.063)
Segment size	0.697***	0.750***	1.059***	-0.575***	-0.653***	-0.753***	1.624***	1.676***
	(0.090)	(0.094)	(0.119)	(0.169)	(0.170)	(0.226)	(0.382)	(0.398)
Segment growth	0.085***	0.086***	0.075***	-0.178***	-0.177***	-0.101**	-0.070	-0.076
	(0.012)	(0.012)	(0.018)	(0.062)	(0.062)	(0.049)	(0.093)	(0.092)
Sunk cost	-0.291*	-0.289*	-1.050***	-0.070	-0.091	-1.244***	-0.696	-0.676
	(0.149)	(0.148)	(0.178)	(0.233)	(0.234)	(0.350)	(0.535)	(0.537)
Relatedness	-0.014***	-0.014***	-0.017***	0.012***	0.011**	0.018**	0.018	0.012
	(0.005)	(0.0051)	(0.005)	(0.004)	(0.004)	(0.007)	(0.016)	(0.016)
Operating cash flow	0.691**	0.700**	0.946**	-1.137***	-1.147***	-1.328**	-2.389*	-2.034
	(0.306)	(0.307)	(0.385)	(0.426)	(0.425)	(0.582)	(1.264)	(1.270)
Industry coarseness	-0.025	-0.026	-0.035	-0.038	-0.038	-0.025	0.123	0.131
	(0.021)	(0.021)	(0.021)	(0.034)	(0.034)	(0.035)	(0.082)	(0.083)
Equity to debt	-0.055***	-0.055***	-0.071***	-0.034	-0.037	-0.037	-0.060	-0.047
	(0.020)	(0.020)	(0.025)	(0.027)	(0.027)	(0.037)	(0.095)	(0.092)
Recovery, lagged			-0.741***			0.967***	0.514***	0.539***
			(0.079)			(0.093)	(0.181)	(0.183)
ln p			0.642***			0.834***	0.485***	0.511***
			(0.023)			(0.044)	(0.066)	(0.065)
ln θ			-2.046***			1.480***	1.104***	1.437***
			(0.312)			(0.278)	(0.358)	(0.347)
Constant			-2.908***			-0.779**	-7.568***	-8.010***
			(0.205)			(0.362)	(0.680)	(0.732)
Log Likelihood	-8473.8	-8472.7	-1196.5	-4599.1	-4597.0	-1384.2	-470.4	-470.4
AIC	17409.6	17409.4	2421.1	9722.3	9719.9	2796.4	966.9	968.8
Observations	5,266	5,266	5,266	5,266	5,266	5,266	3,952	5,266
N of events	1,362	1,362	1,362	729	729	729	163	163
Frailty term, level [a]			*Firm*			*Segment*	*Segment*	*Segment*

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

All PWP models include industry and time fixed effects.

[a] We selected the level of analysis (business segment, firm, or industry) that accounted for the greatest unobserved heterogeneity in the data.

controlling for firm size and other variables. The inflection point is estimated at 3.43 sibling units, corresponding to firms with four to five total segments, including the focal unit. These results are consistent with our theoretical expectation that moderately partitioned firms (neither too coarse nor too fine) provide underperforming units with greater internal support. Compared to coarsely partitioned firms, these units appear to retain organisational power, and firms are more motivated to preserve them through broader access to internal resource markets.

At this threshold, the expected median time to shutdown for an underperforming unit is approximately 3.51 years (see Figure 3-2). However, because shutdown is measured based on the last reporting period, the actual termination may occur during the following year—between 3.51 and 4.51 years.

Additionally, the results suggest that firms with finer partitioning, those with more than four to five segments, are more likely to exit underperforming units if poor performance persists. Specifically, firms with six segments (approximately the mean plus two standard deviations) are 29% more likely to shut down a struggling unit compared to those at the moderate partitioning level. This pattern supports the de-escalation of commitment logic (e.g., Burson et al., 2013; Drummond, 2014; Harvey & Victoravich, 2009; Kolev, 2016; Kwong & Wong, 2014; Lowe & Ziedonis, 2006; McCain, 1986; Northcraft & Neale, 1986), suggesting that finer partitioning enables firms to identify and terminate underperforming units more decisively. In such structures, resource reallocation appears to reflect a "winner-picking" approach (e.g., Maksimovic & Phillips, 2002; Stein, 1997), where support is concentrated on higher-performing segments.

Asset sales were relatively rare in our sample, with only 163 observed cases, suggesting that asset sell off is an infrequent response to persistent negative profitability because other firms are

rarely interested in acquiring loss-making businesses. The shared frailty model (Model 7 & 8; Table 3-5) reveals significant heterogeneity in asset sales.[16]

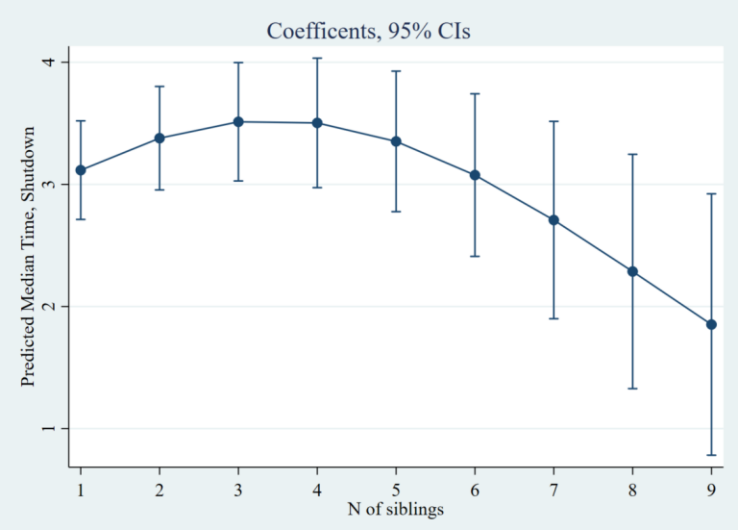

Figure 3-2 Estimated Shutdown Time

Notably, each additional sibling unit increases the likelihood of asset divestment by approximately 19.3% ($\beta = 0.193$, $p < 0.01$), holding firm size and other factors constant.[17] However, we did not find support for the hypothesised U-shaped pattern (Model 8). Instead, the results indicate a linear effect, whereby firms are more likely to divest underperforming units as the number of segments increases, which means that finer partitioning facilitates asset sale. This finding suggests that finer partitioning facilitates asset sales by creating more modular units, which are easier to sell than the larger, more entangled structures typical of coarse partitioning (e.g., Khanna et al., 2018).

Overall, the findings indicate that during underperformance, firms are more likely to pursue shutdowns and very rarely sell assets. We find evidence of a U-shaped relationship between the number of business segments and the likelihood of shutdown, with the highest probability occurring near the recovery inflection point—specifically, in firms with four to five segments. These results provide support for our hypotheses.

[16] We observed significant heterogeneity across business segments, as indicated by the frailty term $\ln(\theta) = 1.104$ ($p < 0.01$); therefore, we report only the model with the frailty specification.
[17] This effect remains robust even when controlling for the absolute size of the segment. Thus, consistent with the logic that more modular units, enabled by finer partitioning, are easier to divest in external markets than larger, more entangled coarse units.

Robustness check

To confirm the robustness of our results we compared multi-segment firms with a matched sample of stand-alone firms, similar to Bardolet et al. (2011). Specifically, we constructed two groups: a 'real' firm sample, consisting of underperforming segments from multi-segment firms, and a 'virtual' firm sample, where the focal segment was replaced with underperforming stand-alone firms operating in the same three-digit SIC industries and having similar asset sizes (within ±0.25 log of total assets). Each real unit was randomly matched to a comparable stand-alone firm. While both samples are similar in size and industry, only the real sample contains actual partitioning and sibling units. By construction, the number of segments should have no bearing on recovery or shutdown outcomes in the virtual sample. This design allows us to isolate the effect of partitioning from other structural or contextual factors commonly correlated with firm complexity.

Using a probit model with time and industry fixed effects and firm-level clustered standard errors (see Table 3-6), we found that the N showed a statistically significant inverse U-shaped relationship with recovery and a U-shaped relationship with shutdown that approached conventional significance levels (p_{N}=0.06, $p_{N\ squared}$=0.008) in the real sample. In contrast, no such effects were observed in the virtual sample. These results strengthen our main finding that partitioning shapes internal decision making and inter-unit dynamics within multi-segment firms, rather than merely reflecting business unit characteristics or industry conditions.[18]

Partitioning, exit versus recovery, and corporate performance

We hypothesised (in H3) that firms with coarse partitioning are better off pursuing recovery strategies, whereas firms with finer partitioning benefit more from terminating underperforming investments. To test this hypothesis, we employed dynamic panel GMM estimation, and the results are reported in Table 3-7

[18] We thank Professor Richard Rumelt for suggesting the matched-sample approach to isolate the effect of main variable.

Table 3-6 Real Firm vs Virtual Firm. Probit Estimates

VARIABLES	(1) Recovery Real firms	(2) Recovery Virtual firms	(3) Shutdown Real firms	(4) Shutdown Virtual firms
N	0.212**	-0.163	-0.207*	-0.068
	(0.103)	(0.122)	(0.109)	(0.111)
N^2	-0.040**	0.028	0.038***	0.006
	(0.016)	(0.019)	(0.014)	(0.017)
Firm size [a]	0.026	0.060	-0.087***	-0.046
	(0.030)	(0.042)	(0.031)	(0.043)
Relative segment size [b]	0.471***	0.315	-0.325	-0.172
	(0.175)	(0.208)	(0.202)	(0.208)
Segment growth [c]	0.108***	-0.071	-0.289***	-0.006
	(0.027)	(0.053)	(0.106)	(0.043)
Size of sunk cost [c]	0.381**	-0.662***	0.233	0.164
	(0.180)	(0.205)	(0.191)	(0.171)
Equity to debt ratio [c]	-0.0180	-0.129***	-0.075**	0.080***
	(0.033)	(0.036)	(0.036)	(0.024)
Industry coarseness [c]	-0.019	-0.165*	0.031	-0.236***
	(0.048)	(0.087)	(0.047)	(0.082)
Recovery, lagged [c]	-0.879***	-2.150***	0.201*	0.533***
	(0.119)	(0.171)	(0.104)	(0.114)
Constant	-4.190***	-1.073	-4.033***	2.123**
	(0.708)	(0.954)	(0.660)	(1.049)
Ind. Fixed effect	Yes	Yes	Yes	Yes
Time Fixed effect	Yes	Yes	Yes	Yes
Observations	1,536	1,536	1,536	1,536
R squared	0.19	0.51	0.14	0.39

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a] Multi-segment firm size was included as a control variable in all models.

[b] The *relative size of the segment* for the virtual firm was measured as the asset size of the stand-alone firm divided by the total assets of the matched multi-segment firm.

[c] Original multi-segment variables were included in models for real firms, while standalone variables were added in models for virtual firms.

Model 1 shows that N has no direct effect on corporate profitability after controlling for other factors, while the linear effect of recovery remains positive (Model 1). However, the impact of N becomes contingent on firms' decisions to exit or recover underperforming units. In Model 2, the interaction between recovery and N is statistically significant ($\beta = -0.0308$, $p < 0.05$) in predicting next-year ROA, alongside a positive main effect of recovery ($\beta = 0.133$, $p < 0.05$). These results suggest that while recovery generally enhances firm performance in the following fiscal year, its benefits diminish—and eventually disappear—as structural partitioning increases beyond four segments.

For instance, in firms with only two segments, successful recovery of an underperforming unit is associated with an 8.1% increase in ROA in the following year (holding firm size and other covariates constant), indicating that recovery is most effective in more coarsely partitioned organisational structures. This finding supports our argument that recovery efforts are particularly valuable when units are coarse and more centrally positioned within the firm. In such cases, the failure to recover even a single unit can trigger substantial reputational spillovers (e.g., Gopalan et al., 2007), increasing the urgency to turn the unit around. Consequently, when successful, recovery amplifies the performance benefits for the firm as a whole.

This pattern is further supported by the long-term, three-year profitability model (Model 5), which identifies an holds until three sibling units (i.e., four segments in total; see Figure 3-3). For instance, firms with only two segments maintain an average ROA of 4.3% post-recovery—indicating that in less partitioned structures, recovery delivers sustained performance gains.[19] Beyond this point, recovery efforts no longer yield meaningful improvements in firm performance; and when firms are partitioned into six or more segments, recovery is associated with a negative effect on overall profitability, all else being equal. This suggests the presence of opportunity costs, resources allocated to recovering underperforming units could instead be reallocated toward more profitable segments (e.g., Klingebiel & Rammer, 2021; Vidal & Mitchell, 2015, 2018). As a result, continued investment in weaker units under finer partitioning may reduce overall corporate performance.

We also find that the performance effects of N depend on whether a shutdown occurs. In Model 3, the interaction term was statistically significant ($\beta = 0.0458$, $p < 0.05$), while the main effect of shutdown was negative ($\beta = -0.107$, $p < 0.05$). This pattern mirrors the recovery model but in the opposite direction, with the turning point again at three siblings (i.e., four segments total;

[19] We estimate whether business recovery in a given year (e.g., 2010) improves firm-wide ROA over the next three years (2010–2012), controlling for average ROA in the preceding and concurrent years (2009–2011). This allows us to isolate the effect of recovery from prior performance trends. Results show a significant negative interaction between recovery and the N (Model 5; $\beta = -0.0152$, $p < 0.05$), indicating that recovery is less beneficial as structural partitioning increases.

see Figure 3-4). While shutdowns are generally associated with performance losses in less partitioned firms (e.g., two segments), they become beneficial when the firm is divided into more than four segments.

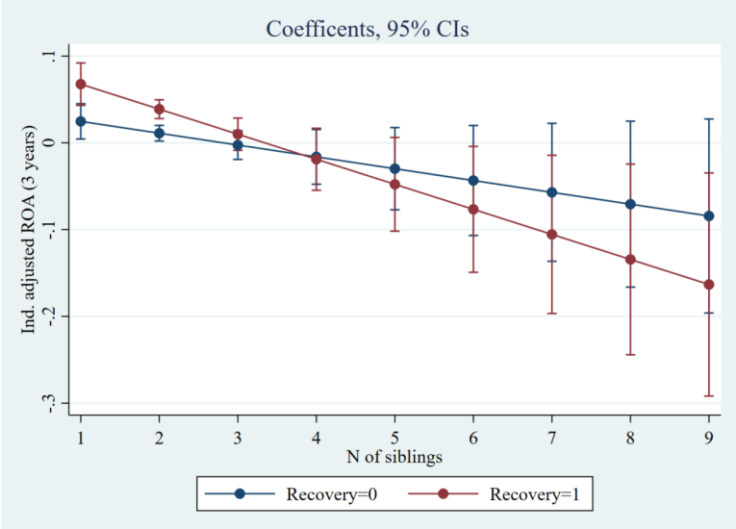

Figure 3-3 Interaction between N and Recovery Status in Predicting ROA (95% CI)

For example, shutting down underperforming units in firms with only two segments (i.e., coarse partitioning) is associated with a 3.4% decline in ROA over a three-year period.[20] This outcome highlights the performance cost of terminating coarse units. As shown in our asset sale analysis in Model 8 in Table 3-5, these firms encounter greater difficulty divesting underperforming units due to tightly bundled, immobile resource configurations (see also Khanna et al., 2018), often leaving shutdown as the only viable exit strategy. Yet, shutdown itself is costly due to limited internal redeployment capacity. Coarse units typically comprise operationally distant, highly specialised and less modular units that are difficult to decouple and re-use within the organisation (Helfat & Eisenhardt, 2004; Khanna et al., 2018; Levinthal & Wu, 2024). As a result, firms with coarser structures tend to suffer performance setbacks, both in the short and long terms, when forced to eliminate such divisions. Overall, this suggests that under coarse partitioning, unit retention and recovery may in fact yield better long-term performance outcomes than exit.

[20] The figure is based on Model 6 in Table 3-7, where the interaction between N and shutdown significantly predicts three-year average ROA ($\beta = 0.0255$, $p < 0.05$), while the main effect of shutdown remains negative ($\beta = -0.0688$, $p < 0.01$).

By contrast, firms with five segments (i.e., finer partitioning) experience a 6.2% increase in ROA in the year following a shutdown, compared to those that retain underperforming units. We further show that this effect persists over time: in Model 6, firms with five segments experience, on average, a 3.6% increase in profitability over a three-year period. This pattern reinforces our earlier findings in Model 5 in Table 3-7, where recovery efforts under finer partitioning were associated with diminished performance. Here, we show that exit decisions in finely partitioned firms are linked to improved corporate performance in both the short and long term. This supports the opportunity cost logic, according to which divestiture frees up corporate resources that can be more effectively allocated to stronger-performing units (Klingebiel & Rammer, 2021; Vidal & Mitchell, 2015, 2018). In contrast, retaining underperforming units in such settings appears to hinder the performance of sibling segments, ultimately reducing overall firm profitability.

Thus, both the recovery and shutdown models consistently indicate that firms with fewer than four segments benefit more from retaining and recovering underperforming units. However, once firms are partitioned into more than four segments, shutdown becomes the more effective strategy—while a four-segment structure represents a neutral threshold. These findings provide strong empirical support for H3.

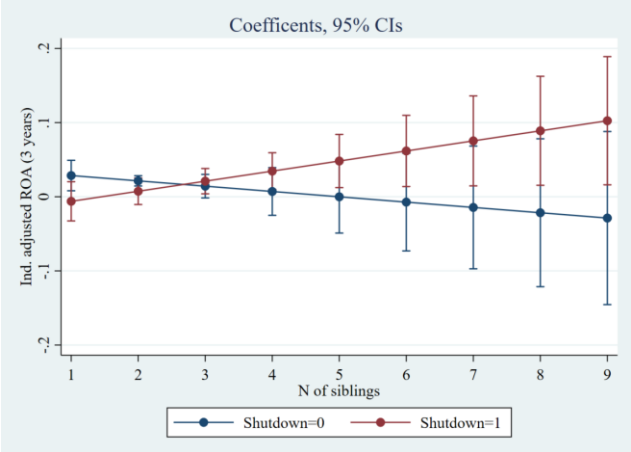

Figure 3-4 Interaction between N and Shutdown Status in Predicting ROA (95% CI)

Table 3-7 GMM Estimation for Ind. Adjusted ROA

VARIABLES	(1) Base model ROA (t+1)	(2) Recovery ROA (t+1)	(3) Shutdown ROA (t+1)	(4) Base model ROA (3 years)	(5) Recovery ROA (3 years)	(6) Shutdown ROA (3 years)
Lag DV	0.162**	0.171**	0.185***	0.675***	0.644***	0.623***
	(0.067)	(0.077)	(0.070)	(0.052)	(0.062)	(0.058)
N	-0.004	-0.007	-0.015	-0.011	-0.013	-0.010
	(0.021)	(0.013)	(0.020)	(0.010)	(0.008)	(0.008)
N × Recovery		-0.030**			-0.015**	
		(0.013)			(0.006)	
N × Shutdown			0.045**			0.025**
			(0.018)			(0.009)
Recovery	0.052***	0.106***	0.040***	0.028***	0.058***	0.031***
	(0.013)	(0.036)	(0.010)	(0.006)	(0.018)	(0.005)
Shutdown	-0.007	0.001	-0.107**	-0.012*	-0.013	-0.068***
	(0.015)	(0.013)	(0.046)	(0.007)	(0.010)	(0.025)
Firm size	-0.069***	-0.051***	-0.048***	-0.031***	-0.027***	-0.030***
	(0.016)	(0.013)	(0.016)	(0.010)	(0.008)	(0.009)
Segment size	-0.167**	-0.173***	-0.177***	-0.081**	-0.078**	-0.072***
	(0.074)	(0.054)	(0.062)	(0.036)	(0.032)	(0.028)
Relatedness	0.004	0.003	-0.000	0.001	0.004	0.003
	(0.006)	(0.005)	(0.004)	(0.002)	(0.003)	(0.002)
Segment growth	0.002	-0.000	-0.003	0.001	0.003	0.002
	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)	(0.005)
Sunk cost	-0.048	-0.085***	-0.043	0.004	-0.021	-0.011
	(0.032)	(0.031)	(0.034)	(0.021)	(0.023)	(0.023)
Operating performance $_{t-1}$	-0.127*	-0.121*	-0.131*	-0.111***	-0.100**	-0.090***
	(0.066)	(0.064)	(0.067)	(0.040)	(0.042)	(0.034)
Equity to debt $_{t-1}$	-0.025***	-0.021***	-0.016***	-0.015***	-0.0155***	-0.014***
	(0.006)	(0.006)	(0.006)	(0.003)	(0.004)	(0.004)
Industry coarseness	0.034***	0.025***	0.024***	0.014**	0.013***	0.013***
	(0.009)	(0.007)	(0.008)	(0.005)	(0.004)	(0.005)
Constant	0.358***	0.296***	0.307***	0.220***	0.207***	0.210***
	(0.091)	(0.068)	(0.086)	(0.056)	(0.046)	(0.051)
Observations	2,014	2,014	2,014	1,823	1,823	1,823
AR (2) test [a]	0.392	0.514	0.441	0.586	0.758	0.563
Hansen test (overid. restrictions) [a]	0.823	0.590	0.509	0.514	0.698	0.399
Difference-in-Hansen [a]	0.885	0.793	0.690	0.301	0.635	0.312
Number of instruments	67	95	108	67	83	108
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of ID	866	866	866	774	774	774

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a] reported is a p-value.

The null hypothesis is that the errors in the first-difference regression exhibit no second-order serial correlation.

The null hypothesis is that the instruments used are not correlated with the residuals.

Discussion

Corporate partitioning and firm response to unit underperformance

This study explores how corporate partitioning influences firm responses to underperformance, particularly decisions to exit or recover struggling units. While prior research offers mixed findings on when multi-business firms pursue recovery versus exit, our study highlights the structural configuration of business units that guides these decisions. Specifically, we argue that the way activities are grouped—whether coarsely, moderately, or finely—shapes the internal power of each unit and its access to resource support, thereby influencing whether firms pursue recovery or exit.

Specifically, at one end of the spectrum are coarsely partitioned firms, typically comprising a small number (e.g., two or three SIC 4-digit segments) of large divisions (Argyres & Lovallo, 2024). In these firms, each unit holds substantial power because its size is closely linked to overall corporate performance (Bardolet et al., 2017; Pfeffer & Salancik, 1974). Research also shows that such units are often seen as unique and irreplaceable (Burson et al., 2013), and individuals are more likely to remain committed to them, even when they are failing (Kwong & Wong, 2014). However, with only a few sibling units in the portfolio, coarsely partitioned firms face constraints in mobilising internal support, as there are fewer sources from which to reallocate resources. Unlike moderately partitioned firms, where recovery efforts can be reallocated from more sibling segments, coarsely structured firms often struggle to sustain the level of investment needed for turnaround, making the pace of recovery slower.

Moving toward the middle of the spectrum, units within moderately partitioned firms, typically comprising four to five business segments (based on 4-digit SIC codes), appear to occupy a structural "sweet spot". In these firms, underperforming units benefit from head office support, as they remain influential enough to attract managerial attention, while the presence of more sibling

segments increases the likelihood of receiving internal resources. Indeed, we find that firms are less likely to shutdown these units, suggesting they retain enough influence to justify continued investment. At the same time, a broader segment base expands the firm's internal resource market (Duchin & Sosyura, 2013; Hoang et al., 2024; Rajan et al., 2000; Scharfstein & Stein, 2000), which is reflected in faster recovery compared to coarsely partitioned units. As a result, these units are more insulated from termination, even in the face of sustained losses.

However, as partitioning becomes finer (Argyres & Lovallo, 2024), typically in firms with six or more segments, this advantage diminishes. Units tend to diminish in size and relative power, making it more difficult for underperforming divisions to attract internal resources, despite the presence of a potential internal resource market. Prior research suggests that finer partitioning intensifies internal competition (e.g., Knott & Turner, 2019) and fragments managerial attention (e.g., Christen et al., 2009), prompting decision makers to rely on simplifying heuristics (Morrin et al., 2012). In particular, we observe a more pronounced "winner-picking" approach, wherein firms prioritise performance-based metrics to guide allocation decisions (Maksimovic & Phillips, 2002; Stein, 1997). This is reflected in the reduced likelihood of recovery efforts for underperforming units, relative to coarsely or moderately partitioned firms. Moreover, finer partitioning tends to narrow the scope of unit activities, strengthen incentive alignment and reduce vulnerability to lobbying by lower-level managers (Argyres & Lovallo, 2024; Guadalupe & Wulf, 2010; Rajan & Wulf, 2006). As a result, weaker units that fail to meet performance thresholds are more likely to be shut down or sold (i.e., treated as expendable) rather than candidates for continued support.

Implications for corporate performance

Next, we examined the performance implications of these decisions in both the short term (one year) and the longer term (three-year average), with both horizons yielding consistent patterns across all analyses. Our findings indicate that the recovery of coarsely partitioned units is positively associated with overall corporate performance, likely because it helps minimise negative spillover

effects (Gopalan et al., 2007). In other words, failure in one segment can damage the reputation and credibility of the entire firm, thereby reducing the performance of sibling units. This is consistent with findings by Gopalan et al. (2007), who show that the failure of a major business group can erode public trust and reduce the profitability of affiliated groups by up to 32%.

Other scholars also argue that coarse unit termination is particularly costly because such units are difficult to divest or repurpose internally (e.g., Helfat & Eisenhardt, 2004; Karim, 2006; Sakhartov & Folta, 2014; Sakhartov & Folta, 2015). Supporting this view, our analysis shows that firms with coarse units are significantly less able to sell assets, even after controlling for firm size and division size. As a result, shutdown becomes the primary, if not only, feasible exit strategy. However, even shutdown proves challenging in these settings, as coarse structures often involve tightly coupled operations (e.g., shared technologies or economies of scope) and limited modularity (e.g., Helfat & Eisenhardt, 2004; Khanna et al., 2018; Levinthal & Wu, 2024). Consistent with this, we find that shutting down units in coarsely partitioned firms leads to large declines in corporate performance. These findings suggest that, in such contexts, firms' efforts to retain and recover underperforming units are economically justified.

It is also worth noting that while moderate partitioning (i.e., four to five segments) appears to facilitate the retention and recovery of underperforming units, we find no evidence that such recovery translates into improved overall corporate performance (either in the short term or over a three-year horizon). By contrast, exit becomes the more effective strategy once firms are partitioned into four or more segments. This pattern is consistent with concerns about potential misalignments in internal capital allocation (Rajan et al., 2000; Scharfstein & Stein, 2000; Sengul et al., 2019). For instance, at five segments (just beyond the identified threshold) shutting down an underperforming unit is associated with a 6.2% increase in next-year ROA and a 3.4% improvement in long-term profitability. This suggests that, even when recovery succeeds, the effort involves significant opportunity costs, diverting resources that could have been allocated more productively elsewhere (Lim & Audia, 2020; Vidal & Mitchell, 2015, 2018).

In contrast, under finer partitioning, firms appear to benefit more from exiting rather than recovering underperforming units. This finding supports the logic that exit can free up financial resources for more productive reallocation (Lim & Audia, 2020; Vidal & Mitchell, 2015, 2018), and our results show that such reallocation is positively associated with subsequent improvements in corporate performance.

Theoretical contribution

This paper contributes to three theoretical streams: *escalation of commitment*, *corporate socialism*, and the *behavioural theory of the firm*. First, while prior experimental studies on escalation of commitment suggest that more partitioning facilitates de-escalation from underperforming units (e.g., Burson et al., 2013; Drummond, 2014; Harvey & Victoravich, 2009; Kolev, 2016; Kwong & Wong, 2014; Lowe & Ziedonis, 2006; McCain, 1986; Northcraft & Neale, 1986), we find that such outcomes are relatively rare in practice. Firms often continue to cross-subsidise struggling units, especially under coarse and moderate partitioning, where these units retain considerable internal influence.

Second, in relation to corporate socialism (Scharfstein & Stein, 2000), our findings offer a more nuanced perspective on the assumption that supporting underperforming units inherently reflects internal market inefficiencies. When partitioning is coarse, terminating such units often incurs substantial costs and generates negative spillover effects, rendering cross-subsidisation and recovery the more rational response. We also show that finer partitioning weakens the lobbying power of lower-level managers, thereby reducing internal political pressures to sustain inefficiencies and facilitating more objective performance-based decision making.

Finally, we extend the behavioural theory of the firm (Cyert & March, 1963; Posen et al., 2018) by demonstrating that both the direction of problemistic search (whether resource-intensive or resource-freeing (e.g., Kuusela et al., 2017)) and its intensity are shaped by the firm's internal partitioning structure (Posen et al., 2018). Specifically, we show that under coarse and moderate

partitioning, firms tend to engage in a resource-intensive search aimed at achieving survival-driven aspirations, often by reallocating support to struggling units. By contrast, finer partitioning is associated with resource-freeing behaviour, whereby underperforming units are required to justify continued funding; if unsuccessful, divestment becomes the preferred response. In terms of search intensity, our findings indicate that moderately partitioned firms invest more sustained effort in diagnosing and supporting underperforming units, whereas firms with finer partitioning exhibit more immediate and decisive action, often opting for exit rather than extended evaluation or support (summary of the theoretical contributions is provided in Appendix Table 3-A4).

Conclusion

This study advances our understanding of how corporate partitioning shapes firm responses to underperforming business units and the consequences of those responses for corporate performance. Moderately partitioned firms are most likely to pursue recovery, benefiting from a broader internal resource market. In contrast, coarsely partitioned firms are less able to support recovery due to limited redeployment capacity, while finely partitioned firms tend to favour exit, driven by weaker unit influence and stricter performance-based evaluation. We find that recovery improves performance only in coarsely partitioned firms, whereas exit enhances profitability in more finely partitioned structures. These findings refine theories of escalation, corporate socialism, and behavioural decision-making by linking structural partitioning to firms' patterns of resource allocation.

Appendix

Table 3-A1 Segment Shutdown and Change in an Assets Size

Change in a Firm Assets $_{(t+1)}$	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
Shutdown	-.05	.012	-4.21	0	-.074	-.027	***
Relative segment size	-.069	.013	-5.42	0	-.094	-.044	***
Firm size	.001	.002	0.37	.714	-.004	.005	
M&A expenses	.074	.069	1.07	.286	-.062	.211	
Divestments earnings	.353	.133	2.66	.008	.093	.614	***
Constant	-.003	.044	-0.08	.937	-.09	.083	

Mean dependent var	0.014	SD dependent var	0.217
R-squared	0.144	Number of obs.	4737
Ind. & time fixed effects	Yes		
Akaike crit. (AIC)	-1347.945	Bayesian crit. (BIC)	22.244

*** $p<.01$, ** $p<.05$, * $p<0.1$

Table 3-A2 Segment Shutdown and Earnings from Discontinued Operations

Earnings from divestment $_{(t+1)}$	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
Shutdown	-.005	.001	-4.04	0	-.007	-.003	***
Relative segment size	-.001	.001	-0.46	.648	-.004	.002	
Firm size	0	0	1.90	.058	0	.001	*
Constant	-.009	.011	-0.85	.397	-.03	.012	

Mean dependent var	-0.000	SD dependent var	0.026
R-squared	0.069	Number of obs.	5086
F-test	1.319	Prob > F	0.000
Ind. & time fixed effects	Yes		
Akaike crit. (AIC)	-22550.974	Bayesian crit. (BIC)	-20773.659

*** $p<.01$, ** $p<.05$, * $p<0.1$

Table 3-A3 Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Recovery	1.000														
(2) Shutdown	-0.237*	1.000													
(3) Asset sale	0.012	0.011	1.000												
(4) N of siblings	-0.011	-0.032*	0.066*	1.000											
(5) Firm size	0.055*	-0.102*	0.110*	0.402*	1.000										
(6) Segment size	0.104*	-0.049*	0.073*	-0.359*	-0.148*	1.000									
(7) Segment growth	0.039*	-0.058*	-0.026	-0.016	-0.004	-0.069*	1.000								
(8) Sunk cost	0.066*	-0.003	0.014	-0.131*	-0.064*	0.207*	-0.050*	1.000							
(9) Relatedness	-0.076*	0.049*	-0.007	0.079*	0.049*	-0.310*	0.095*	-0.063*	1.000						
(10) Operating cash flow	0.003	-0.046*	-0.024	0.028*	0.191*	-0.140*	0.018	-0.163*	0.104*	1.000					
(11) Industry coarseness	0.016	-0.053*	0.077*	0.032*	0.348*	0.150*	0.025	0.091*	0.005	0.064*	1.000				
(12) Equity to debt	-0.068*	0.012	-0.058*	-0.164*	-0.297*	0.021	0.027*	0.016	-0.008	0.024	-0.110*	1.000			
(13) Lag recovery	-0.231*	0.060*	0.017	-0.007	0.005	0.135*	-0.134*	-0.160*	-0.079*	0.053*	0.010	0.012	1.000		
(14) ROA (3 years)	0.135*	-0.013	0.015	0.095*	0.141*	-0.179*	0.008	-0.027	0.075*	0.252*	0.010	-0.046*	-0.091*	1.000	
(15) ROA (t+1)	0.089*	-0.010	0.007	0.078*	0.114*	-0.133*	0.004	-0.037*	0.061*	0.205*	0.015	-0.036*	-0.052*	0.827*	1.000

* $p<0.05$

Table 3-A4 Theoretical Contribution

Perspective	Corporate Socialism	Behavioural Theory of the Firm	Escalation of Commitment
Focus	Resource allocation inefficiencies	Decision making based on aspirations.	Cognitive biases in decision making.
What is consistent	Recovery is the most common response to underperformance, with sibling segments often cross-subsidising struggling units.	Aligned with the theory, firms engage in "problemistic search" when performance falls below aspiration levels, typically drawing on internal resources—often from sibling units—to support recovery.	Firms with a greater number of finely partitioned units are less susceptible to escalation of commitment bias.
What is inconsistent	Cross-subsidisation is not always harmful. In coarsely partitioned firms (e.g., with fewer than four segments), recovery efforts are more often associated with improved corporate performance, whereas termination can be costly and may involve negative spillover effects.	Search during periods of resource availability (i.e., support from sibling segments) does not always lead to resource-intensive exploration. In finely partitioned firms, such searches may be deprioritised even when support is available.	The relationship between the number of segments and exit decisions is not strictly linear and does not hold in the majority of cases. The assumption that more alternatives (i.e., more segments) facilitate de-escalation is only supported when the firm has finer partitioning (N > 5).
Key Contribution	Resource allocation efficiency is shaped not only by firm behaviour but also by corporate partitioning; inefficiencies are most likely at moderate levels of partitioning (i.e., four to five segments). In finely partitioned firms (e.g., N > 4–5), firms tend to adopt a winner-picking logic, reallocating capital more closely in line with unit performance.	The direction and intensity of "search" behaviour depend on partitioning structure, influencing how and when firms pursue recovery. At moderate levels of partitioning, firms engage in resource-intensive search, actively seeking to recover underperforming units. In contrast, under finer partitioning, firms shift toward less resource-intensive, divestment-oriented search, favouring exit over recovery.	Commitment to underperforming units is often supported by sibling segments; in firms with coarse or moderate partitioning, this support tends to sustain recovery efforts rather than prompt exit.

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CHAPTER 4 : FROM MUTUAL FORBEARANCE TO MULTIFRONTAL RIVALRY: CONDITIONAL LIMITS TO STRATEGIC RESTRAINT

Kamzabek, T., & Lovallo, D. (2025). From mutual forbearance to multifrontal rivalry: conditional limits to strategic restraint. *Working paper*.

FROM MUTUAL FORBEARANCE TO MULTIFRONTAL RIVALRY: CONDITIONAL LIMITS TO STRATEGIC RESTRAINT

Introduction

When Unilever, Procter & Gamble, and Henkel compete in personal care and household products, their rivalry extends well beyond a single product line. These firms confront each other across a broad range of categories, from detergents to skincare to hygiene, forming multi-market contact (MMC). This overlap raises the strategic stakes, as a competitive move in one market can trigger retaliation in another (Bernheim & Whinston, 1990; Edwards, 1955). For decades, researchers have viewed MMC as a source of *mutual forbearance*—a tacit or explicit agreement among rivals to avoid aggressive actions that might trigger costly cross-market retaliation (Bhattacharjea & Sinha, 2015; Evans & Kessides, 1994; Hughes & Oughton, 1993; Pilloff, 1999; Scott, 1982, 1991; Yu & Cannella Jr, 2013).

Thus, MMC is traditionally seen as a deterrent to rivalry. However, recent evidence shows this is not always the case (e.g., Diestre et al., 2023; Domínguez et al., 2021; Roy & Sarkar, 2022; Ryan-Charleton & Galavan, 2024; Stephan & Peters, 2013; Theeke & Lee, 2017; Varadarajan, 2023). Some scholars argue that repeated aggressive encounters may trigger competitive arousal (e.g., Kilduff, 2019; Kilduff et al., 2010), leading to excessive investment and competitive over-reaction (e.g., Andrevski & Ferrier, 2019; Malhotra, 2010; Malhotra et al., 2008; Yu et al., 2022). This raises a central question: when do firms deviate from mutual forbearance? Inconsistent empirical support across studies suggests there are important gaps in research attempting to answer this question. Our study attempts to understand these gaps, identifying three contextual conditions under which mutual forbearance has yielded.

First, the effect on mutual forbearance of the number of markets in which a firm overlaps with its rivals remains unclear. While one set of rivals may be equally exposed to retaliation, the distribution of that exposure can differ significantly. Some firms may overlap in only two markets, while others may face the same rival across five. Prior literature generally shows that MMC rivals are prone to herding bias (imitating each other's market entries) and therefore extend the number

of contacts (e.g., Hsieh & Vermeulen, 2014; Lieberman & Asaba, 2006) on the premise that repeated encounters promote reciprocal deterrence and restraint (e.g., Dekeyser et al., 2021; Feinberg & Larson, 2024; Gimeno, 1999; Hughes & Oughton, 1993; Lin & McCarthy, 2023; Schmitt, 2018). Other evidence suggests that imitation can also trigger competitive aggression, as firms interpret each other's moves as an invasion of their territory (e.g., Baum & Korn, 1999; Bhattacharjea & Sinha, 2015; Byford & Gans, 2014; Fuentelsaz & Gómez, 2006; Stephan & Boeker, 2001). In such cases, the number of overlapping markets, despite similar levels of sales-at-risk, may critically influence whether firms choose restraint or retaliation.

Second, we examine the role of non-overlapping markets (markets where firms do not directly compete with their multi-market rivals) as a largely under-explored dimension of MMC. Since not all multi-market rivals operate in the same set of markets, firms may also maintain positions in segments free from the presence of a rival. For instance, although Procter & Gamble, Unilever, and Henkel compete across several product categories, each also maintains exclusive positions in certain markets: P&G in grooming, Unilever in ice cream & nutrition, and Henkel in adhesives. However, an open question is how firms coordinate their actions across shared and non-overlapping markets. Some studies suggest that firms tacitly avoid aggression in shared markets and refrain from invading each other's exclusive domains (e.g., Bhattacharjea & Sinha, 2015; Byford & Gans, 2014; Chuang & Thomson, 2017; D'Aveni, 2002), instead redirecting investments toward uncontested segments where competitive behaviour is less constrained (e.g., Chuang & Thomson, 2017; D'Aveni, 2002). However, other studies argue that firms may continue to monitor their multi-market rivals (Arie et al., 2017; Chen et al., 2007; Malhotra et al., 2008) and remain poised to attack if conditions shift (e.g., Arie et al., 2017; Fu & Iyer, 2019). In such cases, profits generated in non-overlapping markets may serve as resource reserves, enabling firms to fund targeted investments or strategic incursions into contested markets.

Third, we examine industry growth as a potential boundary condition that warrants further empirical testing. Although earlier studies link high growth to reduced investment due to fear of

retaliation (e.g., Bernheim & Whinston, 1990; Fernandez & Marin, 1998; Scott, 1982; Sengul & Gimeno, 2013), more recent work suggests a different pattern. Specifically, growth may attract greater investment based on the premise that expanding markets offer surplus demand beyond what existing rivals can capture (Fu & Iyer, 2019), particularly in the context of technological emergence and disruptive innovation (e.g., Hsu & Cohen, 2022; Roy & Sarkar, 2022).

These inconsistencies warrant a more comprehensive analysis, particularly in the context of investment behaviour. Unlike pricing, where the majority of studies identify a direct relationship between MMC and forbearance (i.e., price premiums), the relationship between MMC and investment (Capex, R&D, market entry, etc.) remains empirically elusive (e.g., Arie et al., 2017; Baum & Korn, 1999; Fuentelsaz & Gómez, 2006; Greve, 2006; Greve & Mitsuhashi, 2004; Haveman & Nonnemaker, 2000; Hsieh & Vermeulen, 2014; Ryan-Charleton & Galavan, 2024; Ryu et al., 2020; Scott, 1982; Vonortas, 2000, etc.). To address this, we revisit the mutual forbearance hypothesis by examining how firms allocate capital expenditures across overlapping and non-overlapping product markets. Drawing on a panel of S&P multi-segment firms, we operationalize MMC through three granular measures: (1) sales-at-risk, capturing the proportion of a firm's sales exposed to retaliation when investing in a focal industry (Sengul & Gimeno, 2013); (2) industry importance to rivals, measured as the share of rivals' total sales generated in the focal industry, indicating the extent to which firms aggressively target each other's key markets; (3) rivals' market dominance, proxied by the collective market share held by multi-market rivals in the focal industry, capturing the intensity of competitive pressure in markets dominated by multi-market firms. To test competing predictions and clarify the direction of effects, we interact each MMC measure with three key moderators: (1) the number of markets in which the firm operates; (2) the ROA of non-overlapping markets; and (3) industry growth.

Our findings reveal that, *first*, mutual forbearance tends to erode when rivals operate in numerous overlapping markets, as excessive contact undermines tacit collusion on market allocation. *Second*, even when non-overlapping is profitable, firms are motivated to reallocate

resources from these non-overlapping markets to finance businesses in more contested arenas. *Third*, while firms often limit investment in markets with high exposure to retaliation, they nonetheless invest aggressively in high-growth industries that are important to their rivals, suggesting that growth in a rival's key markets draws greater attention and lessens caution. Moreover, this aggressive approach frequently leads to over-investment and the eventual exit of challengers from the rival's key markets (unless those challengers operate in profitable non-overlapping markets). In other words, aggressive moves increase the risk of failure, but firms with strong profit in non-overlapping markets are better positioned to support their operations in shared markets.

In the following section we explore the theoretical and empirical background to MMC research, providing context to our study and identifying gaps in the research field to date.

Theoretical and Empirical Background

Motivated by empirical inconsistencies in previous studies, we revisit the mutual forbearance hypothesis to better understand how internal capital allocation decisions interact with MMC. We examine this question by focusing on three contingencies, each detailed in the subsections below. Specifically, we identify contexts in which the stability of mutual forbearance becomes contrasting, as internal and external conditions introduce pressures that may undermine tacit restraint: (1) the number of markets raises the question of whether forbearance holds under extensive overlap; (2) the profitability of non-overlapping markets, which can serve as a source of resources used to invest in overlapping markets; (3) industry growth, which influences firms' future-oriented incentives and creates a dilemma as to whether to escalate competition or exercise restraint.

Multi-market contact and number of markets

The concept of MMC, and its implications, was first introduced by Edwards (1955), who observed that large conglomerates competing across numerous markets might restrain aggressive behaviour to avoid retaliation. Building on this foundational insight, subsequent research (Feinberg, 1985; Sengul & Gimeno, 2013; Sohn, 2001; Yu & Cannella Jr, 2013) has developed ways to quantify the intensity of MMC, often by examining the extent to which a firm's sales are exposed to competitive pressure due to overlapping market presence. These studies consistently find that as such exposure increases firms are more likely to maintain tacit collusion to avoid triggering costly cross-market retaliation.

For example, when evaluating whether to increase investment in a focal industry, firms consider how much of their own sales may be vulnerable to retaliation. That is, aggressive investment in the focal market could trigger retaliation, potentially putting at risk up to 70% of a firm's total sales located in other business segments, a concept captured by the sales-at-risk

measure used by Sengul and Gimeno (2013).[21] For one firm, this 70% exposure may stem entirely from a single overlapping market, whereas another firm may face similar exposure across three different markets (see Table 4-1). Thus, while two firms may have the same overall level of multi-market exposure, the structure of that exposure can vary significantly.[22]

Table 4-1: Two Example Firms with Identical Sales-at-Risk but Different Exposure Structures

Firm A, overlapping markets	Sales share in the firm	*Firm B, overlapping markets*	Sales share in the firm
Industry 1 (original)	30%	Industry 1 (original)	30%
Industry 2	70%	Industry 2	40%
		Industry 3	20%
		Industry 4	10%
MMC sales-at-risk	**70%**	**MMC sales-at-risk**	**70%**

For our hypothetical Firm A, this risk is concentrated. Its heavy dependence on Industry 2 (70%) makes it especially vulnerable to retaliation in that segment if a rival retaliates in response to aggression in Industry 1. This asymmetry in exposure, where the rival holds more influence in Industry 2, creates a deterrent effect, making Firm A more likely to exercise restraint (e.g., Bernheim & Whinston, 1990; Gimeno, 1999). Firm B, in contrast, faces a more distributed but still significant threat. Although it is less dependent on any single market, it shares exposure with its rival across three additional segments—Industries 2, 3, and 4. This broader overlap arguably provides the rival with multiple avenues for retaliation (based on a measure developed by Sengul & Gimeno, 2013). Thus, even without deep dependence on any one industry, Firm B remains exposed to a wide range of potential punitive actions. But does more overlap always (or ever) lead to more restraint?

A growing body of research supports the view that mutual forbearance is strengthened as firms increase their exposure across a greater number of overlapping markets. Broader contact enhances mutual observability (Greve, 2008; Yu & Cannella Jr, 2013) prompting firms to intentionally maintain or expand MMC with rivals (Knickerbocker, 1973; Lieberman & Asaba,

[21] In the original measures of sales-at-risk or risk of retaliation, Sengul and Gimeno (2013) weighted the calculations by the proportion of multi-market rivals present in each market. This approach is also conceptually similar to the measure used by Feinberg (1985). For simplicity, our illustration assumes that the firm faces a constant number of competitors across markets. We focus primarily on Sengul and Gimeno (2013)'s measure, as their study closely aligns with ours in both context and objectives, examining capital expenditure decisions by multi-business firms under multi-market competition.

[22] Note, these are stylised examples of focal firms and are not intended to represent direct rivals.

2006), especially when there is some degree of pre-existing overlap (Greve, 2006; Hsieh & Vermeulen, 2014). Specifically, across a broad range of studies in industrial organisation and strategic management, scholars have found that greater market overlap is associated with price premiums (see Appendix, Table 4-A1). This overlap is often interpreted as a deliberate strategy to protect performance across the firm's broader portfolio (Dekeyser et al., 2021; Feinberg, 1985; Heggestad & Rhoades, 1978; Hughes & Oughton, 1993; Jayachandran et al., 1999; Kim & Singal, 1993; Lin & McCarthy, 2023; Scott, 1982). Accordingly, firms with extensive MMC tend to be less likely to initiate direct attacks and exit shared markets (Barnett, 1993; Baum & Korn, 1996, 1999; Boeker et al., 1997; Dekeyser et al., 2021; Upson et al., 2012).

Yet empirical studies reveal that mutual forbearance can erode when firms become too inter-connected, suggesting that overlap may also breed competition rather than restraint. One such view posits that rivals firms tacitly agree not to encroach on certain markets, effectively dividing spheres of influence (e.g., Bhattacharjea & Sinha, 2015; Byford & Gans, 2014). However, as the number of overlapping markets increases, this tacit collusion (to avoid invading each other's market(s)) may be violated, undermining the stability of the relationship. For example, prior to 1968, the Australian brewing industry was regionally segmented, with each state dominated by one or two brewers who avoided entering each other's markets (Merrett, 1998). This equilibrium began to unravel when Courage Brewery, based in New South Wales, built a greenfield plant in Melbourne to challenge Carlton & United Breweries (CUB) in its home territory. Although Courage's venture failed, it signalled a shift, regional boundaries became increasingly permeable. By the late 1970s, formerly regional brewers expanded interstate or merged, and by 1985, nearly all had been merged or absorbed into two national conglomerates: CUB (owned by Elders IXL) and Bond Brewing (owned by Bond Corporation), which together controlled 90% of the market. With geographic consolidation complete, competition shifted to branding, product innovation,

and marketing.[23] Kilduff (2019) further theorises that rivalry may intensify over time, as repeated competitive encounters foster personal or emotional investment, shifting decisions beyond purely rational economic logic (e.g., Kilduff, 2014; Kilduff et al., 2010; To et al., 2018).[24] Supporting this view, empirical studies have found that firms become less likely to enter new overlapping markets when some degree of MMC is already established (Baum & Korn, 1999; Fuentelsaz & Gómez, 2006; Haveman & Nonnemaker, 2000; Klein et al., 2020). These patterns are commonly interpreted as evidence that firms fear retaliation, prompting restraint from further entry.

Complementing these findings, Mester's (1987) study of the US savings and loan industry shows that more contact is associated with lower profitability and increased market share instability. Recent evidence from diversified banks (Hoang et al., 2021), supports this view, showing that MMC among diversified firms reduces vulnerability to retaliation due to the ability to shift resources across business units, thereby weakening the deterrent effect typically associated with MMC.

Therefore, as firms overlap in more markets, a competitive tension arises: on the one hand, greater overlap expands the scope of mutual influence (deterring aggressive moves in any single market); on the other, it increases the risk that firms will encroach upon each other's presumed exclusive territories or violate tacit market allocations. As summarized in the Appendix, Table 4-A1, most prior studies consistently find that excessive MMC is associated with premium pricing (e.g., Dekeyser et al., 2021; Feinberg, 1985; Gimeno, 1999; Hughes & Oughton, 1993; Kim & Singal, 1993; Lin & McCarthy, 2023; Schmitt, 2018), although some studies report contradictory evidence (e.g., Ma et al., 2019; Mester, 1987). While prior research has predominantly focused on pricing effects, investment behaviour under MMC (e.g., market entry and exit, product launches, R&D, Capex, etc.) remains less understood and yields more mixed empirical findings. Because

[23] Similarly, Ma et al. (2019) show that intense multimarket contact between Qantas and Virgin Airlines, across 72 domestic routes, undermined tacit collusion. Overlapping operations exposed both carriers to retaliation, leading to repeated fare cuts and price wars. This rivalry proved financially damaging; Qantas, for instance, reported a record A$2.8 billion loss in 2013–2014.

[24] These patterns emerge not only in market entry decisions but also in R&D alliances, where product market overlap undermines cooperation by eroding trust, limiting knowledge exchange, and reducing collaborative innovation (e.g., Runge et al., 2022; Theeke & Lee, 2017).

investment decisions reflect longer-term strategic commitments and involve higher uncertainty than pricing adjustments, they offer a richer and more complex window into how firms navigate multi-market rivalry. This complexity motivates our shift in focus toward a more comprehensive and multi-dimensional assessment of investment responses under extensive MMC.

Multi-market contact and non-overlapping segments

Building on the above, when the number of overlapping markets is limited, the strategic role of non-overlapping markets under MMC becomes particularly salient yet remains relatively under-explored (e.g., Chuang et al., 2018).

As discussed in that precious section, scholars have suggested that firms can sustain collusion, whether tacit or explicit, by selectively avoiding entry into some of each other's markets, thereby maintaining a stable competitive balance (Bhattacharjea & Sinha, 2015; Byford & Gans, 2014). Extending this logic, some firms may treat non-overlapping markets as de facto exclusive territories and deliberately redirect their growth strategies away from contested arenas toward markets with fewer or no multi-market rivals (Barnett, 1993; Chuang & Thomson, 2017; D'Aveni, 2002). Chuang and Thomson (2017) empirically examine this pattern, arguing that such strategic redirection should erode the competitive position of single-market firms operating in isolated markets. Their findings support this view, suggesting that while MMC fosters restraint in overlapping markets, it may also incentivise opportunistic expansion into non-overlapping segments.

However, the stability of these collusive patterns, especially when non-overlapping markets become highly profitable, remains uncertain. Some studies challenge the assumption that rivals consistently avoid shared markets and instead focus exclusively on non-overlapping domains. Arie et al. (2017) argue that non-overlapping markets offer greater flexibility in resource allocation, enabling firms to shift investments between shared and non-overlapping markets based on competitive dynamics. When firms perceive that a multi-market rival is vulnerable, they may

reallocate resources toward overlapping markets to capitalise on the rival's weakness.[25] Similarly, Fu and Iyer (2019) show that while firms tend to respect each other's 'turf" under resource constraints, the accumulation of resources encourages more opportunistic, rent-seeking behaviour that is, attempts to capture rivals' market share or even invade key territories. Gimeno and Woo (1999) further demonstrate that non-overlapping markets can generate cost efficiencies through economies of scope, such as across airline routes, which may further incentivise aggressive investment when such advantages can be leveraged to outperform competitors. In the case of Australia's brewing duopoly, CUB and Lion Nathan still retain distinct regional strongholds (e.g., CUB in Victoria, Lion Nathan in some smaller regions), yet both engage in aggressive competition in New South Wales, a market where neither holds a dominant position (Merrett, 1998).

Taken together, these studies suggest that even when firms tacitly collude, competitive aggression may persist. Firms with resource advantages in exclusive markets may be more inclined to launch direct challenges in shared markets, potentially triggering conflict with rivals. In this way, profitability in non-overlapping markets may reactivate competitive rivalry, challenging the common assumption that firms focus their aggression on single-market rivals while avoiding provocation in shared markets. The array of conflicting theoretical arguments and empirical findings highlights that the impact of profits in non-overlapping markets on mutual forbearance remains an open and important question for further investigation. Appendix, Table 4-A2 summarises these conflicting results.

Multi-market contact and industry growth

Another tension arises when firms operate in high-growth industries that promise substantial returns but are also characterised by intense competition. On the one hand, internal resource markets tend to favour subsidiaries in high-growth industries, where the marginal returns

[25] Arie et al. (2017) also note that MMC is structurally compelled to concentrate resources in shared markets due to limited redeployment options elsewhere. This finding is in direct contrast to the logic of Chuang and Thomson (2017), who suggested that greater MMC encourages investment in non-overlapping markets.

on investment are typically highest. These markets offer opportunities for expansion and innovation, and firms are incentivised to act aggressively to pre-empt competitors and capture first-mover advantages. On the other hand, aggressive moves in high-growth markets can disrupt the delicate balance of mutual forbearance. Because such moves reduce the opportunity for rivals to act, they increase the likelihood of triggering retaliatory responses—not just in the focal market, but across other shared domains.

In industrial organisations, when demand is growing rapidly, firms place greater value on future profits, making the threat of punishment for cheating more powerful (Bernheim & Whinston, 1990; Fernandez & Marin, 1998; Scott, 1982). Therefore, collusion is easier in high-growth markets because the long-term loss from retaliation outweighs the short-term gain from cheating (Bernheim & Whinston, 1990). In this case, firms may intentionally restrain investment, even in attractive segments, to avoid triggering retaliation in other markets (Haveman & Nonnemaker, 2000; Sengul & Gimeno, 2013). As Bernheim and Whinston (1990, p. 9) note, MMC enables firms to "shift punishment power" from high-growth to more mature markets, potentially harming profit units elsewhere in the portfolio. Building on this logic, Sengul and Gimeno (2013) provide empirical evidence that French firms reduce capital investment in high-growth markets when exposed to greater MMC, suggesting that fear of costly retaliation discourages aggressive expansion.

However, only recently has this perspective begun to be revisited. Fu and Iyer (2019) develop a formal economic model showing that when firms invest in value creation, they expand overall market/demand surplus, thereby making the market more attractive. Because this surplus is non-excludable, that is, the benefits of investment cannot be fully captured by the one firm, rivals can free ride by reallocating competitive resources to capture the resulting demand growth. This dynamic may create a strategic incentive for firms to attack a rival's key or home market, particularly when they believe that the expanded demand is sufficient to sustain intensified competition.

Roy and Sarkar's (2022) study of the disk drive industry also challenges the universality of mutual forbearance by showing that its logic does not hold in industries undergoing a technological boom. In emerging and high-tech industries—where innovation opportunities are abundant and firms can secure returns through patents or first-mover advantages—the incentives to compete aggressively outweigh the disciplining effect of MMC. Roy and Sarkar (2022) argue that mutual forbearance emerges more clearly in the maturity phase of technological evolution, when innovation slows, appropriability weakens, and the threat of reciprocal retaliation increases. In contrast, during the period in which an industry is emerging and growing, firms behave opportunistically and are less likely to restrain competition for fear of cross-market retaliation.

In parallel, Hsu and Cohen (2022) extend this logic by examining MMC across industries, building on Christensen's theory of disruptive innovation. In the context of disruptive innovation (Christensen, 2013; Christensen & Bower, 1996), where it is unclear what customers want or how to serve them profitably, incumbents often struggle to recognise the potential value of such markets because they rely on established routines, dominant customer relationships, and familiar technologies. However, Hsu and Cohen (2022) show that cross-industry MMC introduces diverse mental models and strategic logics, enabling firms to reframe their understanding of customer needs and market potential. This cognitive reframing, according to Hsu and Cohen (2022), is particularly valuable during periods of rapid industry growth, when innovation uncertainty is high and firms must adapt quickly. In this way, MMC may not restrain rivalry but instead serve as a catalyst for market entry, the adoption of disruptive innovations, and the pursuit of emerging growth opportunities.

In sum, the motivation for firms to collude during periods of industry growth remains; while some studies suggest a positive relationship between industry growth and collusion (Bernheim & Whinston, 1990; Fernandez & Marin, 1998; Scott, 1982; Sengul & Gimeno, 2013) others highlight the opposite, showing that growth may instead fuel competitive aggression (Fu &

Iyer, 2019; Greve, 2008; Hsu & Cohen, 2022; Roy & Sarkar, 2022). Table 4-2 summarises these conflicting results.

Table 4-2 Contrasting Interrelations Between Industry Growth and Mutual Forbearance

Context or measurements	**Outcome: Mutual Forbearance**	**Outcome: Competitive Aggression**
Price	(Bernheim & Whinston, 1990) (Fernandez & Marin, 1998)	
Investments (capex, capacity expansion, market entry)	(Sengul & Gimeno, 2013) (Scott, 1982)	(Fu & Iyer, 2019) (Hsu & Cohen, 2022)
Product development, innovation output		(Roy & Sarkar, 2022)
Outcomes as an indicator of forbearance or defection (sales heterogeneity, profit, market share)	(Bernheim & Whinston, 1990) (Fernandez & Marin, 1998)	(Greve, 2008)

Methodology

Sampling

We collected data on business market/segment, firm, and industry-level variables from COMPUSTAT, focusing on S&P 1500 companies operating in at least two business markets and are multi-market rivals (i.e., they share at least two SIC four-digit industry). Each segment must have observations spanning a minimum of two consecutive years between 2009 and 2018, a period chosen to capture post-financial crisis and pre-COVID-19 economic conditions. We excluded financial firms (SIC 6000–6999), utility firms (SIC 4900–4999), and public administration firms (SIC 9100–9999) because of their different performance metrics and regulations (e.g., Hu et al., 2023). Additionally, we removed business segments with incomplete or conflicting accounting data, such as zero depreciation, negative capital spending, negative or zero assets, and sales below $1 million.[26] Our final sample consisted of 3,066 segment-year observations across 867 distinct business segments. Our unit of analysis is the business segment or market level, which allows us to directly observe capital allocation patterns, specifically, which markets receive greater internal investment and which are deprioritised, aligning with the MMC measures described below.

Measures of multi-market contact

We used three different measures of MMC, each capturing a different aspect of how firms respond to multi-market rivals in the industry: (1) firm's *sales-at-risk*, operationalized as the share of a firm's sales located in other shared markets excluding the focal segment; (2) *market dominance of multi-market rivals* (excluding the focal firm); (3) the *importance of the industry to rivals*, measured by the share of rivals' total sales that comes from the focal industry. These three measures are included because they reflect complementary aspects of competitive dynamics. *Sales-at-risk* indicates the importance of the focal market to the focal firm; *importance to rivals* captures how critical is the focal market to multi-market rivals; and *rival dominance* reflects the intensity of competitive pressure or

[26] Capital reallocation across segments becomes challenging as units reach a certain size.

opportunity stemming from the presence of strong multi-market rivals. Further details on each measure are discussed below. All these predictors are lagged by one year to mitigate concerns about simultaneity and to ensure the temporal ordering of predictors and outcomes.

Firm's sales-at-risk

Sengul and Gimeno (2013) developed this measure based on earlier work (Feinberg, 1985; Gimeno & Woo, 1999; Sohn, 2001). The key idea is that when a firm competes in one market, and also faces the same rivals in other markets, those rivals might retaliate—not in the original market, but in other shared markets. The risk becomes higher when a large portion of the firm's operations comes from those connected markets—because retaliation could hurt more of the firm's operations. So, the more sales a firm has in markets outside the focal one, the more is risked by acting aggressively.[27]

For example, put simply, if a firm shares two markets with rivals—one accounting for 20% of its sales and the other for 80%—then investing aggressively in the smaller market risks retaliation in the larger one, thereby putting 80% of the firm's sales at risk. Sengul and Gimeno (2013) refine this concept by weighting the firm's exposure based on the proportion of competitors that are multi-market rivals. The formal measure is as follows:

$$Firm's\ Sales\ at\ Risk_{imt} = \sum_{n \neq m} \left[\frac{C_{imnt}}{N_{nt} - 1}\right] \times r_{int}$$

where r_{int} is the ratio of firm i's sales in market n to the total firm's overall sales. C_{imnt} is the number of rivals that operate in both markets n and m. N_{nt} is the total number of multi-industry firms operating in market n. This approach allows us to weigh a firm's exposure in non-focal markets based on the MMC. The higher the overlap with rivals across markets, the greater the risk of potential retaliation in market m. The *risk* is higher (closer to 100%) when the firm has more

[27] Some firms may maintain a small presence in a market as a strategic foothold, primarily to signal to rivals that they are monitoring the market and prepared to respond if necessary (Upson et al., 2012).

sales in other shared markets (outside the focal industry). In this case, being aggressive in one market may trigger retaliation in those other shared markets—putting a large part of the firm's businesses at risk. In contrast, the *risk* is lower (closer to 0%) when the focal industry accounts for a larger part of the firm's operation or has no multi-market rivals, because there are fewer sales in other markets that rivals could target, and the firm is primarily defending its core business.

Market dominance by multi-market rivals

We take the total sales in the segment by multi-market rivals and divide it by total sales in the segment by all competitors. This shows how much of the industry is dominated by multi-market rivals. A value close to 1 (i.e., 100%) means the market almost entirely consists of multi-market rivals, while a value close to 0 means the firm has very little presence in that segment.

The example in Table 4-3 means that 67% of this segment is controlled by multi-market rivals — they have a strong presence here. This measure is conceptually similar to the MMC density metric (e.g., Barnett, 1993; Greve, 2006) and the market dominance measure (Haveman & Nonnemaker, 2000), as it captures the concentration of multi-market competitors in a given market. However, unlike the density measure, which counts the number of rival firms, our approach uses rivals' sales to reflect their actual dominance. We also exclude the focal firm from the calculation to isolate external competitive pressure. Additionally, this measure can also be interpreted as capturing market opportunity, as a high proportion of single-market firms, and a lower share of multi-market rivals, suggests a market with fewer firms capable of cross-market retaliation, making it a relatively safer environment for investment (Chuang & Thomson, 2017).

Table 4-3 Example for Market Dominance/Share of MMC Rivals

Industry A			
Rivals	Multi-market rival?	Total sales in industry	Total share of MMC rivals
A	Yes	20	
B	Yes	20	
C	No	20	
		60	**40/60=0.67**

Importance of the industry to rivals

This measure shows how important the industry is to a firm's competitors. It is based on how much of the rivals' total sales (by percentage) comes from the focal industry. A value close to 1 indicates that the industry accounts for a large share (nearly 100%) of a multi-market rival's sales, whereas a value near 0 suggests it contributes only a small portion. The underlying logic, drawn from other studies (Bernheim & Whinston, 1990; Gimeno, 1999), is that firms may refrain from aggressive behaviour in markets that are highly important to their competitors to avoid triggering retaliation in their own core markets.[28]

$$\textit{Importance to Rivals} = \frac{\text{Sales of multi-market rivals in the focal market}}{\text{Total (aggregated) sales across all markets of those multi-maket rivals}}$$

The example in Table 4-4 shows a case where the focal firm has three rivals in the segment, and the focal industry constitutes 25%, 75%, and 75% of their total sales, respectively. This shows that 62% of these rivals' sales come from this segment. In other words, this segment is a major part of the rivals' portfolios.

Table 4-4 Example for Importance to Rivals

Industry A			
Multi-market Rivals	Sales in Segment (rivals)	Total Corporate Sales (rivals)	Segment Share (per rivals)
A	5	20	0.25
B	15	20	0.75
C	30	40	0.75
	50	**80**	**50/80=0.62**

Although the three measures are conceptually related, they capture distinct aspects of competitive exposure. In particular, as *Sales-at-risk* measures the position of the focal firm, it does not account for how *important the focal industry is to rivals*, nor does it directly reflect the *market dominance by multi-market competitors* within the industry. While prior studies have used *Sales-at-risk* (or relative measures) to examine the behaviour of conglomerates or multi-business firms (Feinberg, 1985;

[28] Moreover, when the focal industry is simultaneously important to both the focal firm and its rivals, mutual forbearance or tacit coordination may arise, consistent with oligopolistic game-theoretic predictions that firms can attain superior outcomes through co-operative restraint in investment decisions (e.g., Dixit & Nalebuff, 2008).

Sengul & Gimeno, 2013), the *importance of the focal industry to rivals* has remained largely theorised but omitted from empirical testing. *Market dominance* and *importance to rivals* are also not highly correlated (correlation = 0.49), as rivals may dominate a market without it representing a significant share of their overall sales. Conversely, a market may constitute a large portion of a rival's sales, and if those rivals do not hold a dominant position in that market, they may be motivated to invest more aggressively in order to expand their market share and establish dominance.

Empirically, the correlations among the three measures are moderate (i.e., all < 0.5; see Table 4-5), and multi-collinearity is low (VIF < 2), indicating that the measures are sufficiently distinct and can be included in the same model without concern for multi-collinearity.

Table 4-5 Correlation between MMC Measures

Variables	Mean	(1)	(2)	(3)
(1) Importance to Rivals $_{MMC}$	0.27	1.000		
(2) Market Dominance $_{MMC}$	0.59	0.489	1.000	
(3) Firm's Sales-at-risk $_{MMC}$	0.16	0.276	0.452	1.000

Other key predictors

Number of Markets. This refers to the total count of overlapping markets. COMPUSTAT classifies business segments based on a company's reported industry segment or product line. We adopted a standardised criterion by using SIC codes to consolidate reported segments at the four-digit SIC code industry level. Consequently, in our sample, this variable represents the count of overlapping markets, defined as the number of shared four-digit SIC industries between the focal firm and its multimarket rivals. It is worth noting that using SIC codes to consolidate segments is a common and well-established practice for measuring business segment or market and analyzing capital investment patterns (e.g., Bardolet et al., 2011; Biddle et al., 2024; Dickler et al., 2022; Lamont, 1997; Morandi Stagni et al., 2020; Ozbas & Scharfstein, 2010; Wang, 2023).

Profitability, non-overlapping segments. To assess the profitability of a firm's non-overlapping business segments, that is, those that do not share markets with multi-market rivals, we compute a size-adjusted average ROA. Specifically, the metric is calculated as follows:

$$ROA_{unique,t-1} = \frac{\sum \left[\omega_{i,t-1} \times \text{ROA}_{i,t-1}\right]}{\sum \omega_{i,t-1}}$$

where ω is the share of segment *i*'s assets in the previous year relative to the firm's total assets, $\text{ROA}_{i,t-1}$ is the segment's operating return on assets in the previous year. For simplicity, consider the illustrative example below in Table 4-6.

Table 4-6 Illustrative Example of How Profit from Non-Overlapping Markets is Measured

	Presence of MMC	ROA	Relative size (ω)	Weighted ROA	Non-overlapping Segment Size
Segment A	Yes	0.15	0.2	–	–
Segment B	Yes	0.20	0.2	–	–
Segment C	No	0.25	0.2	0.25 × 0.2=0.05	0.2
Segment D	No	0.30	0.4	0.3 × 0.4=0.12	0.4
				0.17 (sum)	**0.6 (sum)**
ROA (non-overlapping) = 0.17/0.6= 0.283					

Here, the firm has two non-overlapping segments (C and D), with a combined asset share of 0.6. The total weighted ROA from these unique segments is 0.17. Using the formula above, this gives us 0.28. This means the implied ROA from the firm's non-overlapping segments is 0.28. In cases where a firm has no non-overlapping markets, we assign a value of 0.[29]

Industry growth. Industry growth is measured as the median two-year growth rate of the focal 4-digit SIC industry, capturing recent performance trends within the sector.

Dependent variable

Capex intensity – this variable captures the capital allocated to each business segment, measured as the ratio of capital expenditures to total assets at the segment/market level.

Control variables

To isolate the effects of MMC on investment behaviour, we include several control variables that capture alternative drivers of resource allocation. First, we account for segment attractiveness, as more profitable or faster-growing business units are naturally more likely to receive investment.

[29] The *Sales-at-risk* $_{MMC}$ measure captures whether the size of the non-overlapping market in a firm's overall sales is large or small, with higher *Sales-at-risk* $_{MMC}$ values indicating a relatively smaller non-overlapping market.

Specifically, we include lagged ROA (i.e., *t*-1) to proxy for business unit profitability and two-year unit growth rate.[30] Second, we control for the performance of the overall corporation using the firm's two-year average operating cash flow over assets, which captures firm-wide investment capacity. Additionally, we include the relative size of the focal business within the corporate portfolio, as larger segments may carry greater power and exert more influence over resource allocation decisions (Bardolet et al., 2017; Pfeffer, 1981).

We also control for firm size (measured as the log of corporate assets), as larger firms are generally more embedded in MMC and exercise mutual forbearance. Finally, drawing on Rumelt (1982) insights, we consider relatedness by linking business units through shared, idiosyncratic core factors such as specialised knowledge, brands, or organisational routines. These connections may increase internal coordination and raise the internal opportunity cost of retaliation, making firms less inclined to disrupt mutual forbearance by attacking rivals in one market at the risk of collateral damage to other related units. This is measured by the ratio of total sales from segments within the same 2-digit SIC industry to the sales of the focal segment.

Descriptive statistics for all variables are provided in Table 4-7. The maximum VIF across all variables is 1.64, indicating that multi-collinearity is not a concern.

Table 4-7 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Capex Intensity $^{\omega}$	.062	.067	0	.355
Importance to rivals $_{MMC}$	.275	.236	0	.992
Sales-at-risk $_{MMC}$	.165	.208	0	1
Market dominance $_{MMC}$	.596	.411	0	1
N of markets	3.013	1.121	2	9
Relative segment size	.362	.275	0	1
Industry growth $^{\omega}$	.06	.115	-.244	.487
Business profitability $^{\omega}$	.105	.159	-.531	.707
Business growth $^{\omega}$	.1	.379	-.418	2.49
Operating cash flow $_{firm}$ $^{\omega}$	.038	.047	-.113	.205
Firm size	8.641	2.079	1.803	13.569
Relatedness $^{\omega}$	1.823	4.054	0	23.456
ROA, non-overlapping $^{\omega}$	.038	.112	-.531	.707

$^{\omega}$ winsorized at the 1st and 99th percentiles

[30] In some cases, firms may lack the motivation to invest in growing markets where multi-market rivals are present, particularly if their own business unit is experiencing low growth. By controlling for unit growth, we aim to ensure that observed investment patterns are not simply driven by internal growth potential but related to MMC. The correlation between business unit growth and industry growth is relatively low (approximately 0.30), and VIFs are below 2, indicating that multi-collinearity is not a concern.

Research design and endogeneity

We applied a dynamic panel model given its suitability for our empirical context. First, we chose this approach because of the strong autocorrelation in our data, where capex in one period is highly dependent on capex in prior periods. Including lagged capex terms helps account for these temporal dependencies and enables more robust hypothesis testing (He & Huang, 2011; Ullah et al., 2018). Second, panel data settings often raise endogeneity concerns due to unobservable firm-level heterogeneity. The dynamic panel generalised method of moments (GMM) estimator addresses this issue by applying first-differencing to eliminate time-invariant effects, thereby mitigating time invariant omitted variable bias (Arellano & Bond, 1991; Roodman, 2009a).[31] Additionally, GMM estimation with robust standard errors enhances the reliability of our estimates in the presence of heteroscedasticity, a common issue in dynamic panel models (Arellano, 2003).[32]

Traditionally, strategy scholars use fixed effects estimation because it can potentially mitigate bias arising from unobservable heterogeneity. However, fixed effect estimates do so under a strong assumption of exogeneity (Wintoki et al., 2012); that is, they rely on an assumption that current explanatory variables (i.e., MMC) are not influenced by past outcomes of the dependent variable (i.e., capex). This assumption often does not hold in MMC settings, where decisions are interdependent over time. For instance, if a firm increased its investment in year t–2, competitors may respond by adjusting their market presence, thereby altering the firm's MMC at t–1. This dynamic feedback creates a correlation between MMC_{t-1} and the error term in the capex equation at t, violating the strict exogeneity assumption. Our system GMM approach uses deeper lags (e.g.,

[31] Notably, we observe that MMC measures are relatively persistent over time—firms tend to face similar levels of MMC across multiple periods. In such cases, fixed effects estimators can suffer from Nickell bias, which arises when a lagged dependent variable (capex) or persistent regressor (MMC) is correlated with the fixed effects term in short panels (Roodman, 2009a). System GMM addresses this issue by transforming the data using first differences (or forward orthogonal deviations) to eliminate unobserved firm-specific effects.

[32] We use the robust two-step system GMM estimator, which includes Windmeijer-corrected standard errors to adjust for potential downward biases in these estimates (Arellano & Bond, 1991; Blundell & Bond, 1998).

t–2, *t*–3, *t*–4) of the MMC variables as instruments, allowing for more robust estimation even when the feedback between investment and MMC exists.

A main drawback of system GMM is the risk of instrument proliferation (or too many instruments) (Roodman, 2009b). Specifically, system GMM uses a system of two equations, a differenced equation and a levels equation, and creates separate instruments for each time period and variable based on available lags. As the number of time periods increases, the number of instruments can grow very quickly. This can cause overfitting, where the model fits the data too well and ends up capturing noise rather than true relationships, which in turn leads to biased estimates and weak statistical tests. To reduce this risk, we limited the number of lags used as instruments to four, following suggestions by (Baum, 2013; Roodman, 2009b). Also, we applied the "collapse" function that creates one instrument for each variable and lag distance, rather than one for each time period, variable, and lag distance (Roodman, 2009b). This option effectively constrains all of the yearly moment conditions so that they are the same.

To specifically address our core question, whether firms defect from mutual forbearance, we examine interaction effects in predicting capital allocation. Specifically, we interact MMC variables with key contextual factors, including the *number of markets*, *ROA of non-overlapping markets*, and *industry growth*, as interaction terms can help reconcile conflicting findings and clarify the direction of relationships when competing mechanisms are at play.[33]

[33] We thank Ajai Gaur for suggesting this technique for examining interaction effects when competing alternative mechanisms exist.

Results

Linear effects of multi-market contact variables

Table 4-8 presents the results of models in which each MMC variable is entered separately (Models 2, 3, and 4). Across all three specifications, the MMC variables are negatively associated with capex intensity. This suggests that firms invest less capital in a segment when: (a) the firm's sales-at-risk due to MMC exposure is high; (b) the focal industry is dominated by multi-market competitors; (c) the industry is particularly important to their rivals. These patterns are consistent with previous studies (e.g., Edwards, 1955; Feinberg, 1985; Scott, 1982; Sengul & Gimeno, 2013) that find that firms may restrain investment in markets where aggressive behaviour could provoke retaliation from competitors, particularly in more strategically significant markets.

However, when all MMC variables are included simultaneously in the same model (Model 4), the results indicate that firms tend to increase capital expenditures in segments dominated by multi-market rivals, except when the industry is important to rivals, in which case the firm faces high sales-at-risk in other shared markets (or the focal industry represents a relatively small share of the firm's overall portfolio).

These findings align more closely with scenarios of asymmetric market presence, where each firm maintains strong positions in different markets (Bernheim & Whinston, 1990; Yu & Cannella Jr, 2013). In such cases, retaliation becomes particularly costly: an aggressive move into a rival's core market is likely to provoke a counter-attack in the aggressor's own important markets. This dynamic is reflected in reduced capital intensity in segments that are highly important to rivals, especially when such investments put a substantial share of the focal firm's overall sales at risk (i.e., when the focal segment is relatively small and the firm's exposure lies in larger, other shared markets). By contrast, the mere market dominance of rivals in the focal segment does not, on its own, appear to deter investment or enforce mutual forbearance.

Multi-market contact and N of markets

Here, we examine how the effect of MMC on capital intensity is moderated by the number of overlapping segments in which the firm operates (Table 4-9). To test this, we interact *Sales-at-risk* due to MMC with the *number of markets* (Model 1). This approach enables us to compare firms with similar overall exposure to multi-market rivals but differing degrees of overlaps specifically, firms operating under high MMC conditions in fewer markets versus those exposed to high MMC across a broader set of markets.

The interaction term is positive and statistically significant ($\beta = 0.0284$; $p < 0.05$), while first-order effects of *Sales-at-risk* are negative ($\beta = -0.0971$; $p<0.01$). This suggests that although firms are generally less inclined to invest in segments that put a higher proportion of their operations at risk, this tendency is not uniform. Greater overlaps (i.e., more markets) with multi-market rivals moderate and eventually reverse this effect (see Figure 4-1). For instance, if investing in a segment puts 60% of a firm's sales-at-risk (i.e., 60% of the firm's other operations are also exposed to the same multi-market rivals), a firm with five overlaps invests capex intensity about 3.44% more in that segment compared to a firm with only two overlapping markets.[34] In other words, when that 60% exposure stems from a single other market, firms tend to follow mutual forbearance. But when the same exposure is distributed across multiple segments, such as four other markets, competition intensifies, and firms become significantly more aggressive in their investments.

We also observe that firms may invest aggressively in markets that are strategically important to their rivals, even when doing so entails high exposure to retaliation.[35] The interaction between *N of markets* and the *importance of the industry to rivals* is also positive and statistically significant ($\beta = 0.023$; $p < 0.05$), while the main effect of importance to rivals is negative ($\beta = -0.0832$; $p < 0.01$),

[34] A 60% sales-at-risk value corresponds approximately to the mean plus two standard deviations.

[35] This rules out the assumption of symmetric competition (Bernheim & Whinston, 1990); mutual forbearance tends to hold when firms possess asymmetric advantages, such as differing levels of market dependence. In our cases, firms may continue to invest in a segment even when it is important to their rivals.

Table 4-8 GMM Estimates for MMC Measures

VARIABLES	(1) Capex intensity	(2) Capex intensity	(3) Capex intensity	(4) Capex intensity	(5) Capex intensity
Lag capex intensity	0.519***	0.405***	0.321***	0.379***	0.449***
	(0.077)	(0.048)	(0.052)	(0.046)	(0.059)
Importance to rivals $_{MMC}$		-0.020**			-0.040***
		(0.010)			(0.014)
Market dominance $_{MMC}$			-0.009**		0.027**
			(0.004)		(0.012)
Sales-at-risk $_{MMC}$				-0.033**	-0.043***
				(0.015)	(0.013)
N of markets	-0.007**	-0.012**	-0.015***	-0.011**	-0.008**
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)
Business size	-0.006	-0.008	-0.017**	-0.011	-0.007
	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Industry growth	0.029***	0.026**	0.035***	0.026***	0.029***
	(0.011)	(0.010)	(0.010)	(0.009)	(0.010)
Business profitability	0.029**	0.031**	0.061***	0.035***	0.046***
	(0.013)	(0.014)	(0.016)	(0.013)	(0.015)
Business growth	0.007**	0.006**	0.006	0.007**	0.0104***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Firm cash flow	0.092***	0.110***	0.115***	0.099***	0.101***
	(0.020)	(0.019)	(0.021)	(0.019)	(0.020)
Firm size	0.002***	0.003***	0.004***	0.003***	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Relatedness	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.019*	0.033**	0.041***	0.032***	0.020*
	(0.010)	(0.013)	(0.014)	(0.012)	(0.012)
AR(2) test [a]	0.675	0.497	0.557	0.458	0.788
Hansen test (overid.) [a]	0.313	0.818	0.621	0.620	0.653
Difference-in-Hansen tests [a]	0.653	0.775	0.504	0.296	0.458
Number of instruments [b]	53	63	43	94	57
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,066	3,066	3,011	3,066	3,011
Number of IDs	867	867	849	867	849

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a] The reported value is a p-value.

[b] The number of instruments depends on the use of the "collapse" option. For certain variables, where collapsing did not improve instrument quality, the analysis was run without it, resulting in a higher instrument count.

Table 4-9 GMM Estimates for MMC and N of markets

VARIABLES	(1) Capex intensity	(2) Capex intensity	(3) Capex intensity
Lag capex intensity	0.393***	0.389***	0.436***
	(0.051)	(0.053)	(0.064)
N × Sales-at-risk $_{MMC}$	0.028**		
	(0.013)		
N × Importance to Rivals $_{MMC}$		0.023**	
		(0.010)	
N × Market dominance $_{MMC}$			0.019**
			(0.007)
N of markets	-0.005*	-0.005*	-0.006**
	(0.002)	(0.003)	(0.003)
Importance to Rivals $_{MMC}$	-0.040***	-0.083***	-0.023**
	(0.010)	(0.028)	(0.011)
Market dominance $_{MMC}$	0.028***	0.005	-0.040**
	(0.009)	(0.007)	(0.020)
Sales-at-risk $_{MMC}$	-0.097***	-0.010	-0.005
	(0.035)	(0.014)	(0.017)
Business size	0.003	0.008	0.010
	(0.006)	(0.006)	(0.006)
Industry growth	0.029***	0.030***	0.033***
	(0.009)	(0.009)	(0.009)
Business profitability	0.052***	0.049***	0.056***
	(0.015)	(0.015)	(0.017)
Business growth	0.010***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)
Firm cash flow	0.103***	0.103***	0.099***
	(0.019)	(0.020)	(0.019)
Firm size	0.001**	0.002***	0.001
	(0.000)	(0.000)	(0.000)
Relatedness	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	0.014*	0.014	0.022**
	(0.008)	(0.009)	(0.010)
AR(2) test [a]	0.627	0.755	0.830
Hansen test (overid.) [a]	0.922	0.844	0.944
Difference-in-Hansen tests [a]	0.584	0.224	0.741
Number of instruments [b]	90	98	72
Time fixed effects	Yes	Yes	Yes
Observations	3,011	3,011	3,011
Number of ID	849	849	849

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a] The reported value is a p-value.

[b] The number of instruments depends on the use of the "collapse" option. For certain variables, where collapsing did not improve instrument quality, the analysis was run without it, resulting in a higher instrument count.

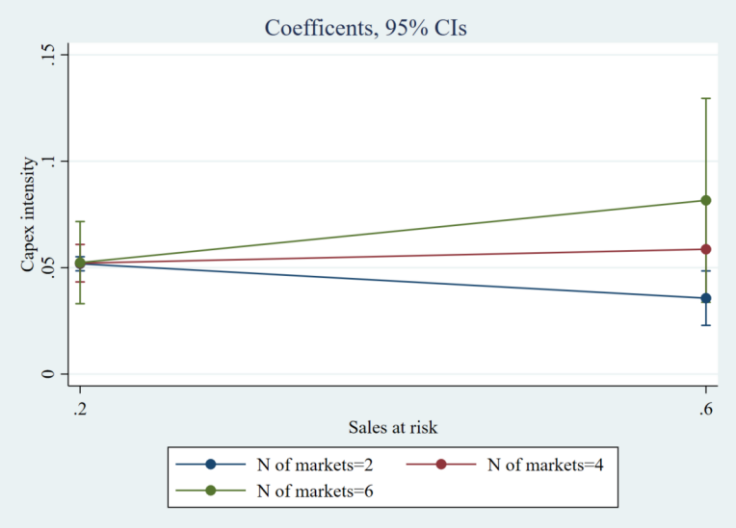

Figure 4-1 Estimates of Capex by Number of Markets and Sales-at-Risk, 95% CI

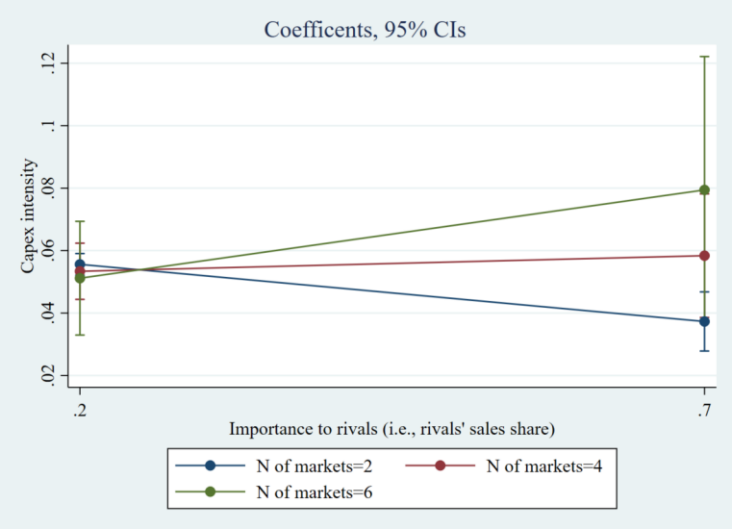

Figure 4-2 Estimates of Capex by Number of Markets and Importance to Rivals, 95% CI

holding *Sales-at-Risk* and other covariates constant (see Model 2). This suggests that although firms generally avoid investing in industries that are important to rivals, this tendency is reversed as the number of markets increases (see Figure 4-2).[36] Additionally, we find that firms with more overlapping markets tend to invest in industries where multi-market rivals have greater market dominance, compared to those where rivals have limited or no presence. This is reflected in the

[36] For example, when the focal industry accounts for 50% of rivals' total sales, a firm with five segments invests approximately 1.0% more capex intensity in that segment compared to when the industry constitutes only 20% of rivals' sales.

positive and significant interaction between N and the *market dominance of rivals* $_{MMC}$ in Model 3 (β = 0.0196; $p < 0.05$; see Figure 4-3).[37]

Overall, as multi-market overlap increases, the ability to sustain mutual forbearance weakens, as a greater number of interaction points heightens competitive tension. Under such conditions, rivals tend to compete aggressively in each other's key markets and in markets where multi-market rivals hold dominant positions, intensifying aggressive competition.

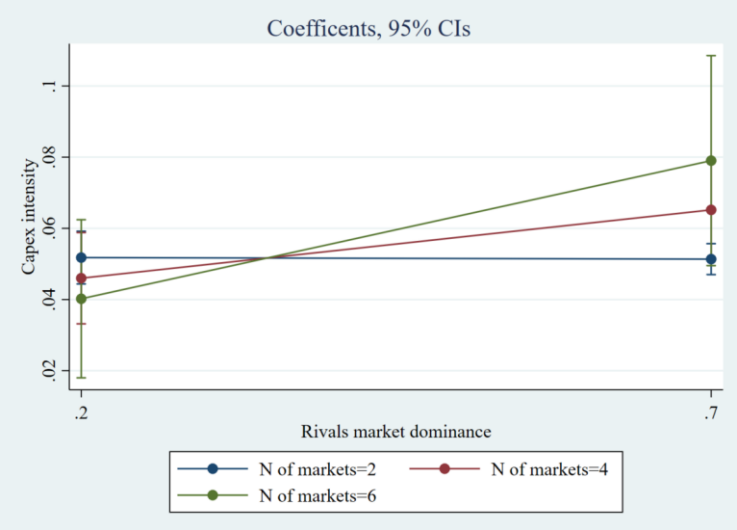

Figure 4-3 Estimates of Capex by Number of Markets and Market dominance of rivals, 95% CI

Multi-market contact and non-overlapping markets

We next examine the role of non-overlapping markets during multi-market competition, specifically, how profits earned in non-overlapping segments influence firms' capital allocation decisions. The results are reported in Table 4-10. We find that the operating *ROA of non-overlapping markets* have a negative effect on capital intensity (Model 1), but this depends on the *sales-at-risk* in the industry (Model 2). When *ROA in non-overlapping markets* is high, firms appear to reallocate capital away from those profitable, isolated markets and toward markets where a substantial share of their overall sales is exposed to rival retaliation. Specifically, the interaction between *non-overlapping segment profitability* and the firm's *sales-at-risk* is positive and statistically significant (β =

[37] For instance, a firm with five segments invests 2.9% capex intensity more in an industry where multi-market rivals control 70% of the market, compared to one where they account for only 20% of industry sales. In contrast, firms with just two segments tend to avoid competition with rivals, investing 3.0% less in industries dominated by them.

0.248; $p < 0.01$), indicating that high profitability in safer markets offsets the deterrent effect of sales-at-risk (first-order coefficient: $\beta = -0.0314$; $p < 0.01$). For example, when the *non-overlapping market* is highly profitable (2SD above the mean), the firm invests 1.1% more in a segment that puts 50% of its overall profit at risk (see Figure 4-4). This indicates that strong performance in less contested markets increases the firm's willingness to take risks—prompting investment even in vulnerable (i.e., smaller) shared markets, even when such moves could provoke retaliation against a firm's core business.

We observe a similar pattern with respect to the market share of multi-market rivals in the industry (Model 3). When the *ROA of non-overlapping markets* is high, firms tend to reduce investment in those isolated markets and reallocate capital toward markets that are dominated by MMC rivals. The interaction between the *market dominance* $_{MMC}$ and *profits from non-overlapping segments* is positively associated with capital intensity ($\beta = 0.145$; $p<0.05$), while the first-order effect of profits is negative ($\beta = 0.116$; $p<0.05$), both coefficients are statistically significant. These findings suggest that high profitability in non-overlapping segments sustains firms' investment in contested industries where multi-market rivals hold a dominant market position. This effect is illustrated in Figure 4-5.

Lastly, we observe that this pattern persists even when the focal industry is highly important to rivals (Model 4). The interaction between *ROA of non-overlapping markets* and the *importance of the industry to rivals* is positive and statistically significant ($\beta = 0.400$; $p < 0.01$), while the first-order effects of *industry importance to rivals* is negative ($\beta = -0.062$; $p < 0.01$).[38] This suggests that, in general, firms avoid investing aggressively in their rivals' key markets. However, when profits from non-overlapping markets are high, resources are redirected toward investment in segments that are important to rivals (see Figure 4-6).

[38] Also, profits from non-overlapping markets ($\beta = -0.170$) are both negative

Table 4-10 GMM Estimates for MMC and ROA of Non-overlapping Markets

VARIABLES	(1) Capex intensity	(2) Capex intensity	(3) Capex intensity	(4) Capex intensity
Lag capex intensity	0.449***	0.415***	0.436***	0.426***
	(0.066)	(0.056)	(0.060)	(0.066)
Sales-at-risk $_{MMC}$ × ROA $_{n}$		0.248***		
		(0.082)		
Market dominance $_{MMC}$ × ROA $_{n}$			0.145**	
			(0.068)	
Importance to Rival $_{MMC}$ × ROA$_{n}$				0.400***
				(0.151)
ROA $_{nonoverlapping\ (n)}$	-0.088**	-0.089**	-0.116**	-0.170**
	(0.038)	(0.037)	(0.056)	(0.071)
Industry importance to rivals $_{MMC}$	-0.045***	-0.034**	-0.041***	-0.062***
	(0.015)	(0.016)	(0.014)	(0.018)
Sales-at-risk $_{MMC}$	-0.042***	-0.031**	-0.036**	-0.043***
	(0.014)	(0.013)	(0.014)	(0.014)
Market dominance $_{MMC}$	0.022*	-0.000	-0.000	0.023*
	(0.012)	(0.011)	(0.011)	(0.013)
N of markets	-0.009**	-0.011***	-0.010**	-0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
Business size	-0.009	-0.005	-0.001	-0.003
	(0.008)	(0.008)	(0.008)	(0.008)
Industry growth	0.030***	0.025**	0.028***	0.026***
	(0.009)	(0.010)	(0.010)	(0.010)
Business profitability	0.066***	0.059***	0.057***	0.068***
	(0.018)	(0.018)	(0.018)	(0.021)
Business growth	0.011**	0.014***	0.012**	0.016***
	(0.004)	(0.005)	(0.004)	(0.005)
Firm cash flow	0.089***	0.095***	0.081***	0.123***
	(0.022)	(0.021)	(0.022)	(0.029)
Firm size	0.003***	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Relatedness	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.026**	0.033**	0.030**	0.023*
	(0.012)	(0.014)	(0.014)	(0.013)
AR(2) test [a]	0.175	0.216	0.214	0.169
Hansen test (overid.) [a]	0.723	0.721	0.558	0.770
Difference-in-Hansen tests [a]	0.712	0.163	0.196	0.466
Number of instruments [b]	74	77	78	71
Time fixed effects	Yes	Yes	Yes	Yes
Observations	3,011	3,011	3,011	3,011
Number of ID	849	849	849	849

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a] The reported value is a p-value.

[b] The number of instruments depends on the use of the "collapse" option. For certain variables, where collapsing did not improve instrument quality, the analysis was run without it, resulting in a higher instrument count.

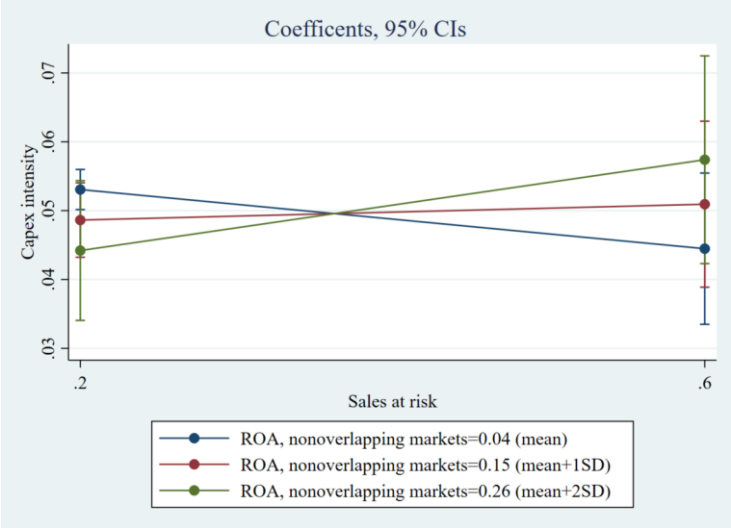

Figure 4-4 Estimates of Capex by Sales-at-Risk and Profit from non-overlapping markets, 95% CI

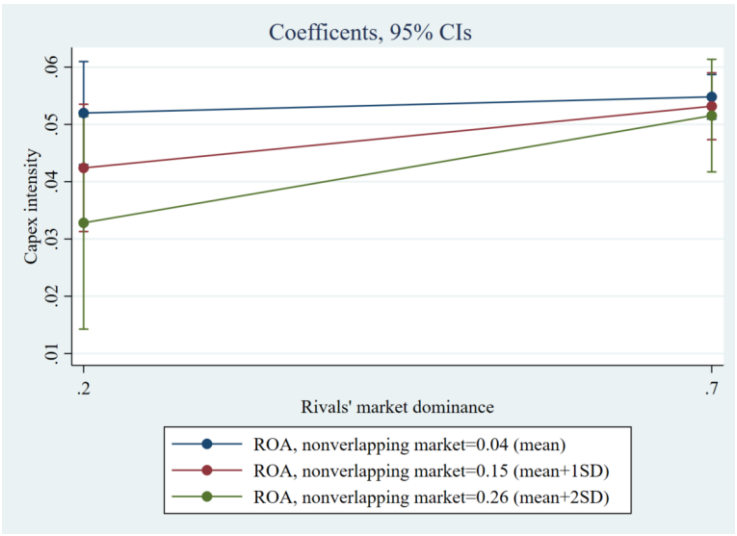

Figure 4-5 Estimates of Capex by Market Share of Rivals and Profit from Non-overlapping Markets, 95% CI

Specifically, when the firm's unique segment is highly profitable (mean plus 2 SD), segments that are important to rivals (i.e., accounting for 70% of multi-market rivals' sales; approximately mean plus two standard deviations) receive 1.16% higher capital intensity compared to those that are less important (i.e., accounting for only 20% of rivals' sales). This suggests that profits from non-overlapping markets fuel investment in segments where the industry is important to rivals, thereby intensifying competitive rivalry. These findings indicate that, when backed by strong performance in non-overlapping markets, firms show a reduced inclination to adhere to tacit collusion and instead are more motivated to assert dominance in their rivals' home/key markets.

Overall, as profits from non-overlapping markets increase, the ability to sustain mutual forbearance weakens. Firms become more inclined to aggressively target each other's key markets in an effort to assert dominance, even when such actions put a substantial portion of their own sales-at-risk.

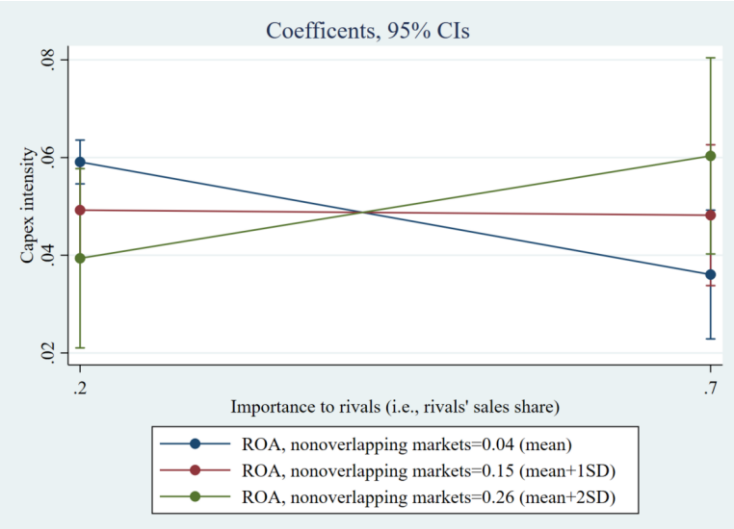

Figure 4-6 Estimates of Capex by Importance to Rivals and Profit from Non-overlapping Markets, 95% CI

Multi–market contact and industry growth

We next examine how industry growth conditions influence the effect of MMC on firms' investments. The results are presented in Table 4-11. When a growing industry puts a substantial portion of a firm's overall sales at risk due to MMC exposure, firms tend to restrain their investment (see Figure 4-7). We find that the interaction between the firm's *sales-at-risk* and *industry growth* is negatively associated with capital intensity (β = –0.0757; p<0.05), while the first-order effect of sales-at-risk remains marginally negative and statistically significant (β = –0.0274; p<0.1). This negative interaction suggests that even in high-growth industries, firms are hesitant to increase capex intensity when those markets place a large share of their total sales at risk due to potential retaliation from multi-market rivals. Thus, even though high-growth conditions normally attract greater investment, when firms face the risk of co-ordinated retaliation from rivals across multiple markets, the incentive to exploit growth opportunities declines. This is consistent with Sengul and

Gimeno (2013), who argue that multi-market rivals are more likely to avoid provocation in strategically sensitive markets to preserve forbearance. See Model 1.

Table 4-11 GMM Estimates for MMC and Industry Growth

VARIABLES	(1) Capex intensity	(2) Capex intensity	(3) Capex intensity
Lag capex intensity	0.396***	0.398***	0.423***
	(0.052)	(0.093)	(0.057)
Sales-at-risk $_{MMC}$ × Ind. Growth	-0.075**		
	(0.038)		
Importance to rivals $_{MMC}$ × Ind. Growth		0.126**	
		(0.059)	
Market dominance $_{MMC}$ × Ind. Growth			0.141***
			(0.041)
Importance to Rivals $_{MMC}$	-0.035**	-0.036**	-0.032**
	(0.014)	(0.014)	(0.013)
Sales-at-risk $_{MMC}$	-0.027*	-0.023*	-0.028**
	(0.016)	(0.012)	(0.012)
Market dominance $_{MMC}$	0.026**	0.002	-0.002
	(0.011)	(0.009)	(0.010)
N of markets	-0.010**	-0.011**	-0.011**
	(0.004)	(0.004)	(0.004)
Business size	-0.008	-0.009	-0.007
	(0.012)	(0.008)	(0.008)
Industry growth	0.046***	-0.024	-0.088***
	(0.014)	(0.022)	(0.033)
Business profitability	0.043***	0.058***	0.057***
	(0.016)	(0.018)	(0.016)
Business growth	0.012***	0.008**	0.011***
	(0.004)	(0.004)	(0.004)
Firm cash flow	0.105***	0.089***	0.104***
	(0.020)	(0.024)	(0.020)
Firm size	0.003***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Relatedness	0.000	-0.000	0.000
	(0.002)	(0.000)	(0.000)
Constant	0.019	0.034**	0.036***
	(0.015)	(0.014)	(0.013)
AR(2) test [a]	0.693	0.740	0.711
Hansen test (overid.) [a]	0.944	0.394	0.757
Difference-in-Hansen tests [a]	0.683	0.173	0.801
Number of instruments [b]	68	64	58
Time fixed effects	Yes	Yes	Yes
Observations	3,011	3,011	3,011
Number of ID	849	849	849

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a] The reported value is a p-value.

[b] The number of instruments depends on the use of the "collapse" option. For certain variables, where collapsing did not improve instrument quality, the analysis was run without it, resulting in a higher instrument count.

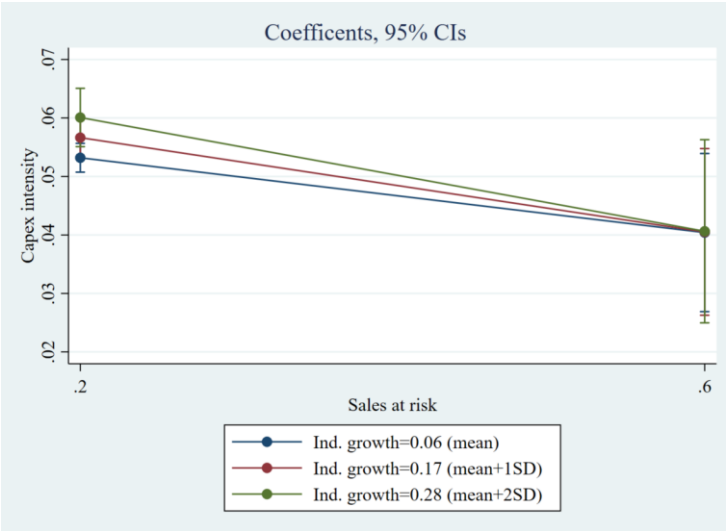

Figure 4-7 Estimates of Capex by Industry Growth and Sales-at-Risk, 95% CI

In contrast, Model 2 shows that, after controlling for the firm's *sales-at-risk* and other covariates, the interaction between *industry growth* and *market dominance* by multi-market rivals is positive and statistically significant ($\beta = 0.141$; $p < 0.01$). This implies that in growing industries dominated by multi-market firms, focal firms tend to increase their capital intensity. Specifically, when industry growth is two standard deviations above the mean, firms invest approximately 1.8% more in capital intensity in industries where rivals control 70% of the market share compared to those where rivals control only 20% (see Figure 4-8).[39] This pattern does not reflect forbearance but rather a rivalry-driven investment response, where the dominance of multi-market competitors signals a strategically valuable and contested market.

In support of this pattern, we find that when a growing industry is *important to rivals*, firms still appear willing to invest in that industry, after controlling for *sales-at-risk* and other covariates. In the Model 3, the interaction between *industry growth* and the *importance to rivals* is positively associated with the focal firm's capital investment ($\beta = 0.126$; $p<0.05$). This effect is especially evident when industry growth is very high, two standard deviations above the mean, where firms invest heavily whether the industry makes up a large share (e.g., 70%) or a small share of rivals'

[39] Notably, because we also control for business unit (segment) growth, this effect cannot be attributed solely to internal performance momentum. Additionally, a difference between 70% market share and 20% market share corresponds approximately to one standard deviation (1 SD).

portfolios (e.g., 5%). In other words, when growth is strong (i.e., 2SD above the mean), firms invest aggressively regardless of how important the segment is to their rivals (see Figure 4-9). Thus, when rivals' key markets experience strong growth, focal firms do not shy away from competition; rather, they are motivated to pursue emerging opportunities, even at the risk of intensifying rivalry. This behaviour reflects firms' sensitivity to rivals' key markets and suggests that firms may place these markets under strategic surveillance as growth opportunities arise.

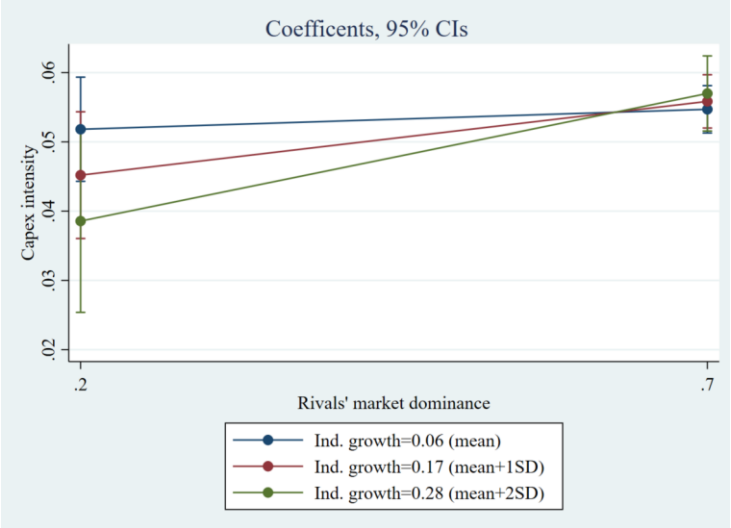

Figure 4-8 Estimates of Capex by Industry Growth and Market Share of Rivals, 95% CI

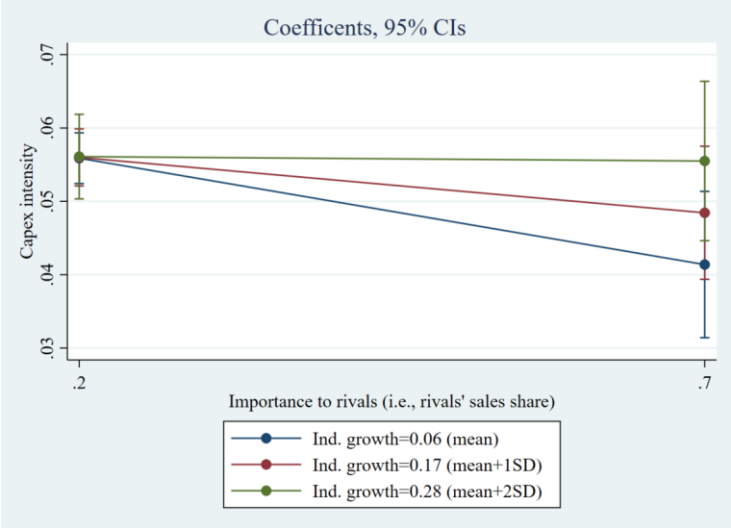

Figure 4-9 Estimates of Capex by Industry Growth and Importance to Rivals

Overall, these findings suggest that while *sales-at-risk* may limit a firm's willingness to invest in a growing market, firms continue to monitor their rivals' key markets closely. Growth in these important markets does not deter investment as mutual forbearance would predict; instead, it appears to trigger more aggressive capital allocation.

Additional test—market exit

Beyond capex intensity, we also examine the consequences of aggressive investments by analysing market exit outcomes in the subsequent year. Specifically, we focus on segments exposed to multi-market rivals and estimate the likelihood of exit by interacting our three core MMC variables with: (1) the number of markets; (2) the ROA of non-overlapping markets; and (3) industry growth indicators.[40] Results are reported in Appendix, Table 4-A4.

First, we find that a higher number of overlapping markets between firms is associated with a greater likelihood of exit from markets that are important to rivals. As noted earlier, firms may initially seek to maintain a foothold in each other's markets; however, extensive overlap increases the likelihood of retaliation. Rivals appear to respond aggressively, pushing the focal firm out of markets that are strategically important to them. Specifically, when a firm overlaps with its rivals in five markets, it is 12% more likely to exit a focal market that accounts for 50% of the rival's total sales, compared to when it overlaps in only two markets (Model 2). This finding supports our earlier result that greater multi-market overlap intensifies competitive investments in rivals' key markets, thereby increasing the risk of forced exit.[41]

Second, the ROA of non-overlapping markets moderates the relationship between exit and two MMC measures (*importance to rivals* and *market dominance of rivals*) in a negative direction,

[40] To identify business exits, we focus on cases where segment discontinuation is accompanied by a decrease in the firm's total assets in the following fiscal year. Since not all segment discontinuations reflect actual market exits—some may result from internal reorganizations, mergers, or reporting changes—we model the expected change in firm assets based on observable non-exit factors such as acquisition expenses, firm ROA, the relative size of the discontinued segment, and overall firm size (see Appendix, Table 3-A3). We then compute the residual asset change as the difference between the actual and expected values. A negative residual indicates an unexpected contraction in firm assets. We classify a true exit as a discontinued segment paired with a negative residual asset change, thereby capturing only those discontinuations that reflect downsizing.

[41] However, we find no evidence of exit in relation to *sales-at-risk* or *rivals' market dominance*.

suggesting that firms are less likely to exit focal markets when their non-overlapping market becomes more profitable (Models 5–6). Specifically, when the ROA of a non-overlapping market is two standard deviations above the mean, the probability of exit from a market highly important to rivals (i.e., accounting for 70% of the rival's sales) decreases by 5.5%. In contrast, we do not find that profitability in non-overlapping segments significantly enhances survival in markets where multi-market rivals hold dominant positions, although the coefficients point in this direction. Notably, the overall exit rate is substantially lower in markets dominated by multi-market rivals than in those where rival dominance is limited, suggesting that firms continue to sustain operations in those markets and maintain a low likelihood of exit.

Overall, these findings suggest that when firms earn higher profits from non-overlapping markets, they are more likely to maintain operations in markets dominated by multi-market rivals and are particularly likely to survive in markets that represent a substantial share of their rivals' sales.

Third, industry growth interacts positively with both *importance to rivals* (Model 8) and *market dominance of the rivals* (Model 9) in estimating market exit, indicating that higher industry growth is positively associated with exit likelihood. Specifically, when industry growth is two standard deviations above the mean, the probability of exit from a market important to rivals (i.e., where rivals depend on it for 70% of their sales) increases by 30% and exit from an industry where rivals control the majority of market share (70%) becomes 1.8% more likely. As previously shown, periods of industry growth tend to intensify investment in rivals' key markets. However, such conditions ultimately increase the risk of exit, as heightened strategic pressure from rivals makes it more difficult for firms to maintain a sustained presence in these contested markets.

Discussion

The central aim of this study is to understand the conditions under which mutual forbearance does not hold in multi-market competition and to reconcile the inconsistent findings of prior research. The study's contributions are primarily theoretical in the context of resource allocation.

Overall, our findings reveal that mutual forbearance can break down even when the risk of retaliation is high. We observe that defections often stem from rivalry-driven motives or competition arousal (e.g., Ferrier, 2001; Hughes-Morgan et al., 2018; Kilduff, 2014, 2019; Kilduff et al., 2010; Malhotra et al., 2008), as firms selectively target segments that are strategically important to their multi-market rivals. Such targeting is frequently met with severe retaliatory responses, and these aggressive investments often result in elevated failure rates, underscoring the behavioural nature of competitive interaction.

First, we find that mutual forbearance is supported by the degree of sales-at-risk but tends to erode as the number of overlapping markets increases. Specifically, we observe that when firms share only a few markets, tacit collusion appears more attainable. However, as the number of overlapping markets grows, firms begin to expect mutual restraint in further encroachments, reflecting a logic of market allocation, where each firm seeks relative independence and aims to preserve exclusive control over specific markets (e.g., Baum & Korn, 1999; Bhattacharjea & Sinha, 2015; Byford & Gans, 2014; Haveman & Nonnemaker, 2000). Yet this equilibrium is fragile. Firms with a history of tacit collusion often mimic each other's market entries, due to herding bias, thereby blurring territorial boundaries (e.g., Hsieh & Vermeulen, 2014; Lieberman & Asaba, 2006). When such imitation is perceived as a breach of tacit collusion, rivals may respond aggressively.

To illustrate this dynamic, we find that firms increase capex intensity in industries that are strategically important to their rivals (i.e., markets on which rivals heavily depend and where they hold dominant positions), even at the risk of exposing a substantial share of their own sales. However, over time, we observe that rivals often succeed in pushing challengers out of their key

markets. Taken together, these findings suggest that as market overlaps increase, firms initially respond with aggressive investment in each other's core markets but eventually begin to retreat from markets that are strategically important to their rivals.

These insights extend a substantial body of work in industrial organisation and strategic management, particularly in studies of product segmentation and diversification (e.g., Coronado et al., 2014; Feinberg & Larson, 2024; Hughes & Oughton, 1993; Vonortas, 2000; Yu & Cannella Jr, 2013). Given the inconsistency in prior findings (as shown in Appendix, Table 4-A1) regarding the effects of MMC on investment decisions, we suggest that an increase in the number of product market contacts may lead to defection from collusion, as firms seek to preserve certain markets as exclusive domains. Methodologically, however, this competitive dynamics may be obscured by commonly used measures such as sales exposure (e.g., Feinberg, 1985; Sengul & Gimeno, 2013). While such measures capture the extent to which a firm places its own sales-at-risk, they do not reflect the number of market overlaps, which can vary substantially even when overall exposure appears similar.

Second, even when firms avoid excessive overlaps and some markets are non-overlapping, such situations do not guarantee mutual forbearance. We find that firms continue to monitor their multi-market rivals, and profitability in non-overlapping segments often serves as a financial base for renewed competitive aggression. That is, firms appear to reallocate resources from stable, less-contested markets to intensify competition in shared ones. Jointly contested markets become disproportionately important, attracting investment even when the risk of retaliation is high.

This pattern aligns with findings from some studies (Arie et al., 2017; Fu & Iyer, 2019) but contradicts Chuang and Thomson (2017). More broadly, the coordination between overlapping and non-overlapping markets remains relatively under-explored in the empirical literature. Arie et al. (2017) theoretically show that the presence of non-overlapping markets provides firms with investment flexibility, for example, enabling them to attack shared markets when rivals are vulnerable and shift resources to non-overlapping markets when multi-market rivals are dominant.

Our findings suggest that, in practice, this dynamic tends to be more one-sided, that is, profitability in non-overlapping markets appears to encourage reinvestment into shared markets rather than reallocation away from them. Our results also support Fu and Iyer (2019), who find that firms with greater financial resources tend to allocate more aggressively toward highly competitive markets. We extend their insight by identifying the mechanism through which non-overlapping markets financially support aggressive behaviour against multi-market rivals. In contrast to Chuang and Thomson (2017), who suggest that MMC firms may behave more aggressively in non-overlapping markets, we find that shared markets often remain the primary battleground. Rather than targeting single-market rivals, firms appear more motivated to assert dominance over their multimarket counterparts.

Additionally, our findings suggest that firms reallocate profits in non-overlapping markets to reduce their failure rates in shared markets. In other words, firms with financial support from less-contested segments are more likely to survive and prevail in competition against their multi-market rivals.

Third, our findings show that firms tend to limit investment in markets where a large portion of their own sales is at risk, consistent with prior work on mutual forbearance (Bernheim & Whinston, 1990; Scott, 1982; Sengul & Gimeno, 2013). However, we also uncover important exceptions to this pattern. Notably, when a high-growth industry is important to multi-market rivals, accounting for a substantial share of their revenues, focal firms appear willing to invest aggressively despite the risks. This suggests that, when rivals are capturing substantial value from a growing market, focal firms may feel compelled to participate in that growth to avoid falling behind competitively. Instead of holding back, firms appear to experience strategic urgency to keep pace (e.g., Fu & Iyer, 2019; Theeke & Lee, 2017), where the visibility of rivals' success in shared arenas intensifies pressure to invest, even at the risk of retaliation. In this sense, MMC not only constrains action through the threat of retaliation but may also amplify motivation to increase investment when rival prosperity signals missed opportunity.

Yet this opportunistic aggression often comes at a cost. When firms act aggressively in markets that are important to their rivals (those with greater rival sales and market share), they are significantly more likely to exit these markets later compared to markets with lower multi-market presence. This suggests that aggressive entry may provoke intense retaliation in that market, ultimately forcing the challenger out. Such over-investment in high-growth markets mirrors patterns of new entrant failure documented in prior research (Camerer & Lovallo, 1999; Dunne et al., 1988; Simonsohn, 2010). In our case, the failure rate increases by a substantial 30% in markets on which rivals are heavily dependent (i.e., accounting for 70% of their sales). For managers, these findings imply that perceived growth opportunities in shared markets may mask the threat of retaliation, making careful evaluation essential.

Conclusion

This study advances our understanding of when and why mutual forbearance breaks down in multimarket competition. While prior research has emphasised the role of retaliation threats in sustaining tacit collusion, our findings show that firms often defy this logic, particularly when they continue to imitate market entries, when non-overlapping markets are profitable, and when rivals' key markets are experiencing growth. However, these aggressive strategies often involve high exit risks, highlighting the possible overinvestments and failures. By identifying the behavioural drivers and structural conditions that influence firm responses across overlapping, non-overlapping, and high-growth markets, this study offers a more nuanced perspective on resource allocation and competitive dynamics in multimarket contexts. We reconcile inconsistent findings in prior research by introducing a more comprehensive measurement approach and by uncovering the mechanisms through which defection from collusion occurs.

Appendix

Table 4-A1 Contrasting Effects of a Greater Number of Overlaps on Mutual Forbearance

Context or measurements	**Outcome: Mutual Forbearance**	**Outcome: Competitive Aggression** [a]
Pricing	*Greater contacts lead to premium pricing* (Dekeyser et al., 2021), (Feinberg, 1985), (Kim & Singal, 1993), (Lin & McCarthy, 2023), (Schmitt, 2018), (Hughes & Oughton, 1993), (Gimeno, 1999), (Fan & Lewis, 2024)	*Greater contacts lead to price competition* (Mester, 1987), (Ma et al., 2019)
Product quality	*Greater contacts lead to reduced quality* (Prince & Simon, 2009), (Wilson, 2023)	*Greater contacts lead to improved quality*
Aggressive actions (Product introduction, marketing, etc)	*Greater contacts lead to reduced actions* (Young et al., 2000; if firms are dissimilar), (Tieying et al., 2009), (Moriguchi & Lane, 1999)	*Greater contacts lead to increased actions* (Young et al., 2000; if firms are very similar)
Investment (R&D, capex, M&As, alliances, etc.)	*Greater contacts lead to reduced investments or increased alliances* (Scott, 1982), (Ljubownikow et al., 2023), (Vonortas, 2000) (Chuang et al., 2018; if alliance formed) (Yu & Lin, 2024), (Ryu et al., 2020) (Anand et al., 2009)	*Greater contacts lead to increased investments or fewer alliances* (Greve & Mitsuhashi, 2004) (Ryan-Charleton & Galavan, 2024)
Market entry	*Greater contacts lead to higher entry* (Knickerbocker, 1973), (Greve, 2006) (Hsieh & Vermeulen, 2014; if rivals previously were under collusion) (Anand et al., 2009; via R&D) (Hsu & Cohen, 2022; when market is ongoing technology boom)	*Greater contacts lead to lower entry* (Stephan & Boeker, 2001) (Alcantara & Mitsuhashi, 2015) (Haveman & Nonnemaker, 2000) (Fuentelsaz & Gómez, 2006) (Anand et al., 2009; markets with strong sales) (Clark & Montgomery, 1998) (Baum & Korn, 1996, 1999) (Klein et al., 2020)
Market exit	*Greater contacts lead to lower exit* (Barnett, 1993), (Baum & Korn, 1996) (Anand et al., 2009; exit from strong sales markets) (Boeker et al., 1997)	*Greater contacts lead to higher exit* (Anand et al., 2009; exit from R&D activities)
Forbearance measured by outcomes (e.g., higher profitability or lower market share volatility as an implication of mutual forbearance)	*Greater contacts lead to improved performance* (Scott, 1991), (Heggestad & Rhoades, 1978), (Coccorese & Pellecchia, 2009), (Pilloff, 1999), (Guedri & McGuire, 2011)	*Greater contacts lead to reduced performance* (Mester, 1987), (Hoang et al., 2021), (Chuang et al., 2018) (Li & Greenwood, 2004; if rivals are dissimilar)

Note: The aforementioned studies incorporate the number of contacts (geographic, segment-based, product-level), either directly or through weighted measures.

[a] we focus specifically on cases classified by the authors as involving a high number of contacts, rather than moderate or low levels.

Table 4-A2 Contrasting Roles of Non-overlapping Markets in Relation to Shared Markets

Context or measurements	**Outcome:** **Firm is aggressive in non-overlapping markets**	**Outcome:** **Firm is aggressive in overlapping markets**
Segment/market/territorial collusion	*MMC leads to reduced invasions and firms aggressive in non-overlapping territories* (Bhattacharjea & Sinha, 2015) (Byford & Gans, 2014) (Valletti, 2003) (Feinberg, 2013)	*MMC leads to increased invasions and firms aggressive in shared territories* (Fu & Iyer, 2019; when budget assymetry exists)
Forbearance measured by outcomes (e.g., single-market firm market share, non-overlapping market profitability, and shared market profitability)	*MMC is associated with higher market share/profitability in non-overlapping markets* (Chuang et al., 2018) (Ren et al., 2011) (Isogai & Shen, 2023; colludes with and punishes defecting single-market firms across nonverlapping markets)	*MMC is associated with higher market share/profitability in shared markets* (Gimeno & Woo, 1999; if firm have cost advantage over rival)
Investments	*MMC is associated with increased investment in non-overlapping markets* (Arie et al., 2017; reduce investments when multimarket rivals are strong)	*MMC is associated with increased investments in shared markets* (Arie et al., 2017; if rivals sence that multimarket rivals are weak)

Table 4-A3 Estimates of Change in Firm Asset Size, Fixed Effects

VARIABLES	Change in an Asset size$_{t+1}$
Acquisition expenses$_{t+1}$	1.670***
	(0.051)
Firm size	-0.174***
	(0.010)
Firm ROA	0.213***
	(0.039)
Business size	-0.036
	(0.031)
Constant	1.508***
	(0.084)
Observations	4,579
Number of Segments	1,190
R-squared	0.359

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4-A4 Estimates of Market Exit, Panel Probit model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Exit probability Number of markets			Exit probability ROA of non-overlapping markets			Exit probability Industry growth		
N	0.202	-0.401	-0.355	-0.057	-0.089	-0.087	-0.052	-0.050	-0.062
	(0.188)	(0.266)	(0.354)	(0.095)	(0.098)	(0.098)	(0.095)	(0.096)	(0.096)
Importance to rivals $_{MMC}$	0.298	-2.523*	0.287	0.241	0.808	0.388	0.306	-0.304	0.381
	(0.494)	(1.473)	(0.491)	(0.514)	(0.527)	(0.497)	(0.491)	(0.548)	(0.498)
Sales-at-risk $_{MMC}$	1.887	0.045	-0.016	0.017	0.080	0.060	0.162	0.094	0.172
	(1.857)	(0.722)	(0.727)	(0.735)	(0.733)	(0.726)	(0.738)	(0.727)	(0.743)
Market dominance $_{MMC}$	-0.047	-0.055	-1.178	-0.029	-0.065	0.203	-0.046	-0.127	-0.600*
	(0.287)	(0.290)	(0.921)	(0.291)	(0.293)	(0.318)	(0.288)	(0.293)	(0.331)
Business size	-0.511*	-0.562**	-0.552*	-0.553*	-0.590**	-0.559*	-0.560*	-0.573**	-0.562*
	(0.286)	(0.286)	(0.288)	(0.288)	(0.293)	(0.289)	(0.288)	(0.291)	(0.294)
Ind. growth	1.475*	1.545*	1.553*	1.546*	1.649*	1.595*	1.841*	-1.864	-3.823*
	(0.858)	(0.856)	(0.853)	(0.852)	(0.864)	(0.853)	(1.037)	(1.501)	(1.959)
Business profitability	0.361	0.322	0.334	0.342	0.378	0.307	0.349	0.280	0.328
	(0.419)	(0.422)	(0.420)	(0.423)	(0.420)	(0.423)	(0.422)	(0.427)	(0.425)
Business growth	-0.357	-0.367	-0.371	-0.340	-0.341	-0.354	-0.339	-0.345	-0.381
	(0.259)	(0.261)	(0.261)	(0.255)	(0.258)	(0.258)	(0.256)	(0.260)	(0.258)
Firm Cash flow	-2.910**	-2.836**	-2.946**	-2.867**	-2.784**	-2.811**	-2.841**	-3.129**	-3.018**
	(1.395)	(1.400)	(1.396)	(1.393)	(1.395)	(1.395)	(1.392)	(1.406)	(1.396)
Firm size	-0.289***	-0.285***	-0.289***	-0.274***	-0.275***	-0.274***	-0.276***	-0.280***	-0.286***
	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.047)
ROA, $_{nonverlaps\ (no)}$	0.944	0.854	0.903	0.681	4.843***	5.318**	0.901	0.840	0.749
	(0.800)	(0.780)	(0.787)	(0.907)	(1.754)	(2.170)	(0.780)	(0.781)	(0.778)
Sales-at-risk $_{MMC}$ × N	-0.803								
	(0.750)								
Importance $_{MMC}$ × N		1.307**							
		(0.638)							
Market dominance $_{MMC}$ × N			0.528						
			(0.411)						
Sales-at-risk $_{MMC}$ × ROA $_{no.}$				1.922					
				(4.099)					
Importance $_{MMC}$× ROA $_{no.}$					-11.97**				
					(4.670)				
Market dominance $_{MMC}$ × ROA $_{no.}$						-5.625**			
						(2.519)			
Sales-at-risk $_{MMC}$ × Ind. Growth							-1.683		
							(3.218)		
Importance $_{MMC}$ × Ind. Growth								11.35***	
								(4.127)	
Market dominance $_{MMC}$ × Ind. Growth									7.128***
									(2.259)
Constant	0.744	2.000*	1.801	1.152	1.108	0.979	1.116	1.451*	1.621*
	(0.865)	(1.023)	(1.100)	(0.840)	(0.845)	(0.855)	(0.841)	(0.852)	(0.861)
$\chi 2$	101.60	101.51	100.21	100.64	102.45	101.94	100.27	104.60	104.74
Prob > chi	**	**	**	**	**	**	**	**	**
Time, Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,460	1,460	1,460	1,460	1,460	1,460	1,460	1,460	1,460
Number of ID	403	403	403	403	403	403	403	403	403

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Estimates are marginal effects averaged across the population (population-averaged)

Table 4-A5 Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Capex intensity	1.000													
(2) Importance to rival $_{MMC}$	-0.008	1.000												
(3) Market dominance $_{MMC}$	0.159*	0.489*	1.000											
(4) Sales-at-risk $_{MMC}$	0.008	0.283*	0.452*	1.000										
(5) N of markets	0.069*	0.046*	0.147*	0.143*	1.000									
(6) Business size	-0.005	0.306*	0.170*	0.012	-0.184*	1.000								
(7) Ind. Growth	0.131*	-0.067*	0.031*	-0.058*	-0.003	-0.029*	1.000							
(8) Business profitability	0.042*	0.043*	-0.013	0.011	0.049*	0.101*	0.059*	1.000						
(9) Business growth	0.117*	-0.022	0.041*	-0.010	0.003	-0.041*	0.330*	-0.030*	1.000					
(10) Firm cash flow	0.269*	0.015	0.077*	-0.008	0.039*	0.042*	0.042*	0.059*	0.077*	1.000				
(11) Firm size	0.087*	-0.014	0.027	0.026	0.323*	-0.192*	-0.009	0.000	-0.013	0.012	1.000			
(12) Relatedness	0.021	-0.074*	0.034*	0.058*	0.059*	-0.355*	0.017	-0.033*	0.005	0.000	-0.015	1.000		
(13) ROA, non-overlapping	-0.057*	-0.131*	-0.173*	-0.069*	-0.144*	-0.076*	0.026	0.231*	-0.026	-0.070*	0.028*	-0.006	1.000	
(14) Market exit	-0.027	-0.006	0.010	0.017	-0.066*	-0.035*	-0.005	-0.023	-0.026	-0.009	-0.133*	0.029	0.008	1.000

* $p<0.05$

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CHAPTER 5 OVERALL CONCLUSION

Together, Chapters 2, 3, and 4 advance our understanding of how behavioural biases shape corporate resource allocation in real-world strategic contexts. Chapter 2 highlights how firms have begun to apply behavioural tools beyond experimental settings, classifying practical debiasing mechanisms used in domains such as resource allocation. Specifically, we illustrate that firms often fall into traps such as inertia and anchoring bias during resource allocation decisions. To address these biases, organisations have implemented techniques such as the CEO piggybank technique as well as several other approaches. However, we also identify a paucity of empirical studies that rigorously test the effectiveness of many other debiasing mechanisms, particularly in complex real-world settings where multiple biases may interact.

Chapter 3 builds on this foundation by examining how organisational structure—specifically, the degree of business unit partitioning—predicts firms' commitment to the loss-making units. Overall, we show that finer partitioning (i.e., dividing the firm into a larger number of smaller units) provides a more effective structural basis for addressing underperformance. By reducing the firm's dependence on any single unit, finer partitioning weakens internal lobbying power, discourages resource-intensive recovery efforts, and facilitates de-escalation of commitment. In doing so, it helps firms better align resource allocation with long-term profitability.

Chapter 4 extends the multimarket competition theory, revealing the conditions under which multimarket contact breaks down. Specifically, we show that firms should be cautious about imitating rivals' market entries (a form of herding behaviour), as this can escalate competitive tension rather than promote tacit coordination. Firms should also be wary of becoming complacent even when market allocation is in place (i.e., collusion in shared markets and when rivals also avoid entering some of each other's markets), as rivals often use profits from non-overlapping segments to fund aggressive actions in overlapping markets. Moreover, we find that

investing in markets that are both important to rivals and experiencing high growth significantly increases the risk of retaliation, including the possibility of being forced out of those markets. Collectively, these findings reveal when multimarket contact can trigger rivalry, rather than suppress it.

Collectively, these chapters demonstrate that integrating behavioural insights with firm-level theories provides a richer, more context-sensitive account of strategic decision-making, helping to bridge the gap between experimental findings and the complex realities of organisational life. We argue that behavioural strategy should be more rigorously tested in real-world contexts and more systematically integrated with established organisational theories to enhance practical relevance.