The Longitudinal Relationship Between Financial Hardship and Mental Health

Joel Alexander Tibbetts

A thesis submitted to fulfil the requirements of the degree of Doctor of Philosophy

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Statement of Originality

This thesis is submitted in fulfilment of the requirements for the degree of Doctor of Philosophy (Medicine) at The University of Sydney.

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

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 sources used have been acknowledged.

Joel Tibbetts

31 December 2025

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Author Attribution Statement

This thesis contains one peer-reviewed publication.

The second chapter – *The longitudinal relationship between financial hardship and mental health - A systematic review of the evidence* – was published in Social Science and Medicine – Mental Health in 2025. I, Joel Tibbetts, am the corresponding and lead author. Each of my four supervisors – Prof Tim Slade, Prof Cath Chapman, Dr Siobhan O'Dean, and Prof Peter Butterworth – share co-authorship on this paper.

All authors were involved in the conceptualisation of this publication.

I, Joel Tibbetts, conducted all article screening, data extraction, quality appraisal, and wrote the original manuscript. All co-authors assisted with secondary article screening and quality appraisal. All co-authors reviewed and approved the final manuscript version for publication.

I confirm that all of the work in this thesis is my own, and any contribution made by others has been explicitly acknowledged.

Joel Tibbetts

31 December 2025

As the lead supervisor for the candidate upon which this thesis is based, I can confirm that the author attribution statement above is correct .

Prof Tim Slade

31 December 2025

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Generative AI Attribution Statement

During the preparation of this thesis the author used ChatGPT for limited assistance with literature search and for assistance with improving one's understanding of R package vignettes. Additionally, title/abstract screening of papers for inclusion in the systematic review (Chapter 2) was assisted with the use of an automated AI screening tool built into the Nested Knowledge AutoLit review software – further details of this are provided in Chapter 2. The author takes full responsibility for the submitted thesis and ensures the work is their own and has used generative AI in accordance with university guidelines and policies.

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Abstract

Mental disorder continues to be a leading contributor to global disease burden and cause of disability worldwide. Concerningly, despite significant expansion of treatment services the prevalence of common mental disorders has remained stable for at least thirty years in many high-income developed countries.

Decades of research have consistently demonstrated the risks posed to mental health of socioeconomic disadvantage. However, it is possible that action upon the recommendations of this work has flagged. In turn, the underlying social conditions driving mental illness have potentially remained under-addressed, and the underlying risk to mental health associated with socioeconomic disadvantage has persisted for sizeable portions of the population.

The majority of work assessing the relationship between socioeconomic disadvantage and health outcomes typically uses relative income poverty lines. However, given the substantial changes that have occurred within the Australian economy since the turn of the century, this approach may not fully capture the extent and depth of disadvantage experienced across the population. Therefore, this body of work seeks to extend the literature, and inform future prevention efforts, by using an outcome-based measure of socioeconomic disadvantage – namely *financial hardship* – and assessing its longitudinal relationship with mental health.

Within this framework, a systematic review of 94 international, peer-reviewed studies, along with a series of cross-sectional and longitudinal analyses using up to 23 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey from 2001 to 2023, demonstrated a substantial and highly robust association between financial hardship and mental health. The prevalence of financial hardship in Australia between 2001 and 2023 was also examined, along with the temporal precedence between hardship and mental health, the extent to which longitudinal profiles of hardship exist, and the relationship of these profiles with mental health. The implications of these findings are discussed.

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Chapter 1 – General Introduction

Overview

Population mental health remains a significant public health concern. Mental disorders represent a leading cause of disability worldwide, and consistently rank as one of the principal contributors to global disease burden and excess mortality (Charlson et al., 2015; Fan et al., 2025; GBD Mental Disorders Collaborators, 2022; Murray et al., 2015; Rehm & Shield, 2019; Vigo et al., 2016; Vos et al., 2015, 2017; Whiteford et al., 2013). Moreover, the prevalence of common mental disorders in many high-income developed countries, including Australia, has remained largely unchanged for at least thirty years. This is despite substantial expansion of treatment, vast increases in mental health expenditure, and extensive reinforcing of the mental health workforce (Jorm et al., 2017; Ormel & Emmelkamp, 2023). Given this, further research is imperative to clarify the mechanisms and pathways – including the causes, correlates, mediators, and risk and protective factors – that contribute to the ongoing and substantial disease burden associated with mental illness.

Whilst various explanations have been examined to explain the existence of this apparent 'treatment-prevalence paradox' (Ormel et al., 2022; Ormel & Emmelkamp, 2023), it is possible that the underlying social conditions driving mental illness have remained under-addressed (Skinner et al., 2022). For example, research over several decades, using various measures of socioeconomic status, has consistently demonstrated that (1) socioeconomic disadvantage represents one of the strongest risk factors for poor mental health, and (2) the prevalence of common mental disorders increases markedly with intensifying socioeconomic disadvantage. (Allen et al., 2014; Compton & Shim, 2015; Kessler & Cleary, 1980; Kirkbride et al., 2024; Phelan et al., 2010; Ridley et al., 2020). Despite these advances in our understanding of how daily social conditions shape health outcomes, it is likely that the underlying risk to mental health associated with socioeconomic disadvantage has persisted, or even worsened, for sizeable portions of the population (Goldman et al., 2018; Saunders et al., 2016; Saunders, 2017; Saunders et al., 2022b).

Very broadly, this thesis seeks to build upon the prevailing literature, by further examining the relationship between socioeconomic disadvantage and mental health to inform prevention strategies. In high-income developed countries, socioeconomic disadvantage has most commonly been assessed using a relative poverty line, set at 50 percent of the median population income (Bray, 2024). Instead, this thesis will examine socioeconomic disadvantage using a measure of financial hardship. In turn, various analytical approaches will be employed to assess the relationship between financial hardship and mental health.

Financial hardship is an *outcome-based* measure of socioeconomic disadvantage that evaluates the direct consequences of insufficient financial resources. It has been elegantly defined by Mack & Lansley (1985) as “an enforced lack of socially perceived necessities”. Evaluating socioeconomic disadvantage using an outcome-based measure, such as financial hardship, holds several advantages over traditional poverty line based assessments (Butterworth & Crosier, 2005; Saunders & Adelman, 2006). Numerous studies have shown that outcome-based assessments of disadvantage provide a superior estimation of the relationship between socio-economic status and mental health (Butterworth, Olesen, et al., 2012; Foulds et al., 2014; Lorant et al., 2007).

Given this, the present body of work aims to extend existing research that has examined the relationship between socioeconomic disadvantage and mental health by: systematically appraising international evidence that has investigated the longitudinal relationship between financial hardship and mental health; assessing the prevalence and correlates of financial hardship in Australia since 2001; assessing the bi-directional relationship between financial hardship and mental health – with respect to temporal ordering, the relative strength of each directional pathway, and the relative strength of the within and between-person components of this relationship; and exploring the degree to which distinct longitudinal profiles of financial hardship experience exist, while quantifying the strength of their relationship with mental health.

This introduction chapter will:

1. *Examine the epidemiology of mental illness in Australia over the past 30 years and establish that prevalence has remained largely unchanged despite considerable expansion of treatment services.*

2. *Review explanations that have been proposed to explain why increased access to treatment has not led to a concomitant reduction in population prevalence of mental illness.*

3. *Summarise research findings detailing the relationship between various socioeconomic risk factors and mental health.*

4. *Provide an overview of the Australian economic context, highlighting significant changes since the turn of the century, and situate the rationale for focusing on financial hardship within this changing environment.*
5. *Outline the theoretical underpinnings of outcome-based approaches to assessing socioeconomic disadvantage – such as financial hardship – and summarise prior research that has examined the relationship between financial hardship and mental health.*

The Epidemiology of Mental Illness in Australia

Robust epidemiological data characterising the mental health of the Australian population has been collected since the mid 1990's. Since this time, a diverse array of surveys has facilitated reliable estimates of nationwide prevalence, incidence, and risk factors for poor mental health and mental disorders. Additionally, this consistent surveillance has informed policies designed to reduce the burden of disease associated with poor mental health and mental illness (Jorm, 2018; Pirkis et al., 2011). However, it has also revealed two concerning trends: (1) mental disorders are common and substantial contributors to national burden of disease estimates, and (2) the overall prevalence of mental disorders has remained largely unchanged over time, despite considerable expansion of treatment services (AIHW, 2023; Harvey et al., 2017; Jorm, 2014; Pirkis et al., 2011; Whiteford et al., 2014).

The 1996 Burden of Disease and Injury in Australia report was one of the first comprehensive, integrated investigations into the population health of Australia. It employed a systematic framework with standardised metrics to quantify the impact of various diseases and injuries on the Australian population (Murray & Lopez, 1996). This seminal report revealed mental disorders to be the leading contributor to years lived with disability (YLD) within Australia across all disease groupings[1]. In addition, mental disorders were also found to be the third leading cause of disability adjusted life years (DALY's), owing to their significant impact on morbidity (behind cardiovascular disease and cancer). Together, mental disorders accounted for 12 percent of disability adjusted life years amongst Australian

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[1] For further detail, see *Table 4.4: Percentage distribution of YLD by main disease category, sex and age group, Australia, 1996*, on page 53 of Mathers et al., 1999.

men, and 14 percent of disability adjusted life years amongst Australian women[2]. Depression was found to be the leading cause of disability burden amongst both men and women across the country – accounting for eight percent of the total non-fatal disease burden[3] (Mathers et al., 1999).

These findings were supported by data collected in the 1997 National Survey of Mental Health and Wellbeing (NSMHWB). This was the first national survey conducted within Australia dedicated to obtaining accurate estimates of the distribution of mental disorders within the population[4]. This survey found that 17.7 percent of Australian adults aged 18 or over had experienced an anxiety, affective, or substance use disorder in the previous twelve months. More specifically, in the 12 months preceding the survey, 9.7 percent of Australian adults aged 18 or over reported experiencing an anxiety disorder, 5.8 percent reported experiencing an affective disorder and 7.7 percent reported experiencing a substance use disorder (Henderson et al., 2000). However, the most salient finding from this survey was the substantial proportion of disease burden that went untreated. Of those reporting *any* mental disorder, just 38 percent were seen by the health service during the preceding 12 months. By specific illness category, only 28 percent of those experiencing an anxiety disorder, 14 percent of those with a diagnosable substance use disorder, and 56 percent of those experiencing affective disorders, had used health services in the preceding 12 month period (Andrews et al., 2001; McLennan, 1998).

Given these findings, interventions designed to interrupt the population prevalence of mental illness were guided by the view that addressing this "treatment gap" – the difference between client-side demand for mental health services, and actual service supply – would reduce the burden of disease associated with mental ill-health and mental illness (Jorm, 2018). However, in 2007 when the NSMHWB was repeated, the proportion of the population who reported experiencing any class of mental disorder in the preceding 12 months had increased to 20 percent (Australian Bureau of Statistics, 2007; Slade et al., 2009). Specifically,

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[2] Again, further detail can be found within *Figure 5.4 Burden of disease (DALYs) by sex and main disease groups, Australia, 1996*, on page 68 of Mathers et al., 1999.

[3] For further detail, see *Table 4.3: Top twenty causes of disability burden: YLD by sex, Australia, 1996*, on page 51 of Mathers et al., 1999.

[4] Prior to the 1997 National Survey of Mental Health and Wellbeing (NSMHWB), Australia had relied on imported prevalence estimates from other countries to gauge likely rates of mental disorder within the national population. Additionally, prevalence estimates that had been generated using local data came from either 1. individuals who had utilised health services (which likely underrepresented the total number of individuals experiencing mental disorders), or 2. samples from a very select subset of communities such as Heyfield, Prahran, Botany Bay, and Canberra (Henderson et al., 2000).

amongst Australians aged between 16 and 85, 14.4 percent reported experiencing an anxiety disorder, 6.2 percent reported experiencing an affective disorder, and 5.1 percent reported the experience of a substance use disorder. Of those who reported experiencing an affective disorder in the previous 12 months, 51 percent were classified as severe.

In 2020 to 2021, the third edition of the NSMHWB was conducted – the results of which, extended prevailing trends identified in the first two surveys. That is, the overall proportion of Australians reporting the experience of a mental disorder in the preceding 12 months had marginally increased again, to 21.4 percent. With respect to specific illnesses, 16.8 percent of Australians reported the experience of an anxiety disorder, 7.5 percent reported experiencing an affective disorder, and 3.3% reported experiencing a substance use disorder in the 12 months prior to the survey (Australian Bureau of Statistics, 2020-2022). With the exception of substance use disorders – which have shown a decreasing trend since 1997 – these figures represent a slight increase compared to the 2007 estimates (Australian Bureau of Statistics, 2020-2022). Building on this, analysis of Kessler Psychological Distress Scale (K10) scores from the 2020-21 survey revealed substantial demographic differences in high or very high psychological distress. Overall, 15.4 percent of Australians aged 16 to 85 reported experiencing high or very high levels of psychological distress. In addition, females were more likely to experience high or very high levels of psychological distress than males (18.6% vs. 12%), and Australians aged between 16 to 34 experienced high, or very high psychological distress at twice the rate of those aged 65 to 85 (20% vs. 9.6% respectively).

Taken together, the three editions of the NSMHWB provide evidence to suggest that no overall improvement in the mental health of Australia occurred between 1997 and 2020-21. Additionally, they point to deteriorations in mental health within specific sub-groups of the population. However, some qualification is needed prior to making direct comparisons between these surveys. Principally, two different diagnostic classification systems were used in the 1997 and 2007 editions to estimate prevalence. The 1997 survey assessed symptoms of mental disorders using version 2.1 of the CIDI, whereas the 2007 survey used version 3.0. Additionally, the 1997 survey assessed symptoms in the previous 12 months, whereas the 2007 survey assessed lifetime symptoms, from which 12-month prevalence was extracted[5]. It should also be noted that the 2020-2021 survey was conducted during the COVID-19

[5] Notwithstanding these constraints, both surveys were designed to have a nationally representative sample of respondents, both used the ICD-10 to assess mental disorders, and both focused on the same set of common mental disorders.

pandemic which may have contributed to elevated rates of poor mental health. Despite this, analysis of K10 scores from the 1997 and 2007 surveys aligned with the aforementioned increasing trend[6] (Reavley et al., 2011). Using separate depression and anxiety indices constructed from the items comprising the K10 scale[7], Reavley and colleagues (2011) found a significant increase in the mean risk of anxiety, and stability in the mean risk of depression between 1997 and 2007. This pattern of results has been replicated within several other studies, comprising distinct samples of the Australian population, that have assessed mental health at varying time points over the past three decades.

For example, estimates derived from the Australian National Health Survey (NHS) evidence a distinct rise in the prevalence of 12-month mental or behavioural conditions, from 9.6% in 2001 to 20.1% in 2017-18[8] (Australian Bureau of Statistics, 2017). Related analyses of K10 data from the 2001, 2004-05, 2007-08, 2011-12, and 2014-15 cross-sections of the NHS have indicated relative stability in the prevalence of 'very high' and combined 'high' and 'very high' psychological distress (Atlantis et al., 2012; Harvey et al., 2017; Jorm, 2018). However, further analyses that included the 2017-18 edition of the NHS have shown evidence of an increase in the prevalence of 'high' and 'very high' psychological distress (Butterworth et al., 2020; Enticott et al., 2022)[9]. Similarly, an analysis of repeated cross-sections of the South Australian Health Omnibus survey (SAHOS) has demonstrated a significant increase in the overall prevalence of major depression from 6.8% in 1998 to 10.3% in 2008 (Goldney and colleagues (2010).

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[6] Assessing changes in K10 scores between the 1997 and 2007 National Survey of Mental Health and Wellbeing overcomes limitations arising from changes in the diagnostic classification used.

[7] K10 items that were separated into the 'Depression Index' included: 1. In the past four weeks, about how often did you feel tired out for no good reason? 2. In the past four weeks, about how often did you feel without hope/hopeless? 3. In the past four weeks, about how often did you feel depressed? 4. In the past four weeks, about how often did you feel that everything was an effort? 5. In the past four weeks, about how often did you feel so sad that nothing could cheer you up? 6. In the past four weeks, about how often did you feel worthless? K10 items that were separated into the 'Anxiety Index' included: 1. In the past four weeks, about how often did you feel nervous? 2. In the past four weeks, about how often did you feel so nervous that nothing could calm you down? 3. In the past four weeks, about how often did you feel restless or jumpy/fidgety? 4. In the past four weeks, about how often did you feel so restless that you could not sit still?

[8] For a detailed breakdown of the prevalence trend in mental and behavioural disorders across all six waves (2001, 2004–05, 2007–08, 2011–12, 2014–15, and 2017–18) of the ANHS, see *Table 1: Summary health characteristics, 2001 to 2017–18 – Australia* at https://www.abs.gov.au/statistics/health/mental-health/mental-health/2017-18#data-downloads. Specifically, refer to sheet three titled *Table 1.3 Summary health characteristics — 2001 to 2017–18, Proportion of persons*.

[9] The prevalence estimates reported by Butterworth et al., (2020) differ from the rates reported by Enticott et al., (2022) – though the increasing trend of very high psychological distress observed is consistent. Specifically, Butterworth and colleagues (2020) reported an increase in very high psychological distress from 3.4% in 2001 to 4.2% in 2017. This is most likely due to the analysis by Butterworth et al., (2020) not standardising the data for demographic changes.

Assessments of the Australian populations mental health using the Household, Income and Labour Dynamics in Australia (HILDA) Survey have also reflected the upward trend in prevalence of poor mental health found within the NSMHWB and NHS. Unlike the NSMHWB and NHS however, which sample repeated cross-sections of the Australian population, the HILDA survey utilises a longitudinal panel design with annual data collection (Wooden & Watson, 2007). This has enabled surveillance of fine-grained trends in a range of mental health outcomes since the start of the 21st century. For example, Butterworth and colleagues (2020) analysed six waves of K10 data from the HILDA survey and reported an increase in the prevalence of ‘very high’ psychological distress from 4.8 percent in 2007 to 7.4 percent in 2017. Similarly, Burns and colleagues, (2020) assessed changes in the SF-36 mental health subscale over 17 consecutive years of the HILDA survey between 2001 and 2017. They also found evidence consistent with substantive declines in the mental health of the Australian population, particularly in analyses that disaggregated by age and sex. Pointed declines in mental health were observed amongst males, and for respondents aged 18-34. Aligning with this, a recent age-period-cohort analysis utilising 20 years of HILDA survey data suggested that overall declines in population mental health within Australia may be accounted for by substantially poorer mental health observed amongst younger cohorts born in the 1980’s, and especially the 1990’s (Botha et al., 2023).

Treatment Expansion within Australia

Collectively, this evidence suggests that there has been no measurable improvement in the population mental health of Australia since the establishment of reliable surveillance in the mid 1990’s. Moreover, with respect to specific sociodemographic subgroups such as younger Australians, it is evident that substantial declines have occurred. Crucially, this pattern has emerged within a context of greater mental health awareness, funding provision, and service availability.

As noted above, one of the key findings from initial assessments of Australia’s population mental health in the mid 1990’s was the large proportion of mental health burden that was going untreated. This insight prompted policy and action designed to address the mental health burden associated with an inability to access efficacious treatment. By many metrics, increases in funding to the mental health sector, service availability, service provision, and service uptake all ensued. For example, Australian government expenditure on mental health increased from $3.1 billion ($176 per capita) in 1992-93, to roughly $13.2 billion ($501 per capita) in 2022-23 (AIHW, 2025a). Between 1992 and 2022-23, the number of full-time equivalent (FTE) staff working within specialised public mental health services increased by over 86% from approximately 80 to 149 per 100,000 of population (AIHW, 2025b).

With respect to specific professions, the number of FTE psychiatrists increased by 60% between 1995 and 2023 from approximately 10 to 16 per 100,000 of population (Australian Institute of Health and Welfare, 2003; National Mental Health Commission, 2025). Similarly, between 2004 and 2022 the number of FTE mental health nurses increased from 68 to 96 per 100,000 of population (a 41% increase) (Australian Institute of Health and Welfare, 2007; National Mental Health Commission, 2025), and between 2011 and 2022 the number of psychologists increased from approximately 84 to 125 per 100,000 (a 49% increase) (Australian Institute of Health and Welfare, 2017; National Mental Health Commission, 2025). Long term trends in the use of pharmacological interventions, such as antidepressant SSRI medication, indicate an increase of 352% from 1990 to 2002 (Mant et al., 2004), and a further 95% from 2001 to 2011 (Stephenson et al., 2013).

In 2006, implementation of the Better Access Scheme enabled publicly subsidised access to evidenced-based psychological treatment through Medicare, Australia's universal public health insurance scheme (Jorm, 2018). In turn, a sharp increase in the uptake of psychological services followed. In just three years the proportion of Australian's living with a diagnosed mental disorder receiving treatment increased from 37% in 2006-07, to 46% in 2009-10 (Whiteford et al., 2014). Accordingly, service use rates increased substantially for psychologists (10.2 to 16.4 per 100,000 of population) and clinical psychologists (4.7 to 8.9 per 100,000 of population)[10] (Pirkis et al., 2011). Extending these trends further, the number of Australians in receipt of publicly subsidised mental health services increased from 5.7% of the population in 2008-09, to 10.6% in 2018-19 (Australian Institute of Health and Welfare, 2020). Current data from 2023-24 indicates that approximately 2.7 million Australians received 12.6 million Medicare-subsidised mental health services. Furthermore, almost 5 million Australians were dispensed 47.3 million mental health-related prescriptions – of which 72% were for antidepressant medication (Australian Institute of Health and Welfare, 2025d).

Prevalence/Expenditure/Service Provision Rest of the World

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[10] See Table 4 on page 23 of (Pirkis et al., 2011) for more detail.

In summary, improved funding of mental health, along with expansions to service availability, provision of treatment, and greater service utilisation has not aligned with an overall improvement in the mental health of the Australian population (Atlantis et al., 2012; Burns et al., 2020; Goldney et al., 2010; Jorm & Reavley, 2012; Meadows et al., 2019; Reavley et al., 2011). However, this finding is not unique to Australia. There has been no detectable decline in the prevalence of mental illness across many high income developed countries, including the United States, the UK, Canada, Finland, Germany, the Netherlands, Japan, and New Zealand, over the last three decades (Baxter et al., 2014; Bretschneider et al., 2018; De Graaf et al., 2012; Ferrari et al., 2013; Filatova et al., 2019; James et al., 2018; Kessler et al., 2005; Keyes et al., 2014; Mojtabai & Jorm, 2015; Mulder et al., 2017; Nishi et al., 2018; Ormel et al., 2019; Patten et al., 2015, 2016; Richter et al., 2019; Simpson et al., 2012; Spiers et al., 2016; Steel et al., 2014; Steffen et al., 2020; Weinberger et al., 2018). Akin to Australia, this is despite significant increases in public expenditure on mental health, and significantly increased rates of treatment (De Graaf et al., 2012; Filatova et al., 2019; John et al., 2015; Jorm et al., 2017; Marcus & Olfson, 2010; Mark et al., 2011; Olfson et al., 2014; Ormel et al., 2020; Saxena et al., 2011; Steffen et al., 2020; Walters et al., 2012)

Treatment-Prevalence Paradox

Given this, several researchers have attempted to reconcile the apparent paradox of increased resourcing and treatment availability failing to catalyse measurable population mental health improvements within high-income developed countries (Furukawa & Kessler, 2019; Jorm, 2014; Jorm et al., 2017; Jorm, 2018; Meadows et al., 2019; Mulder et al., 2017; Ormel et al., 2019, 2022; Ormel & Emmelkamp, 2023). One explanation has questioned whether a true treatment driven reduction in prevalence has been masked by an increased willingness of individuals to disclose symptoms of mental illness. A second explanation has queried whether an increase of false positives is a result of psychiatric concept creep and diagnostic inflation increasingly pathologising normal human distress (Angell, 2011a, 2011b; Frances, 2013; Haslam et al., 2021). Examination of both hypotheses has deemed them unlikely. Principally, due to the absence of evidence indicating a rise in the number of individuals meeting diagnostic criteria for mental disorder in standardised interviews. It has also been argued that both effects are unlikely to be large enough to mask a treatment-driven drop in "true" epidemiological prevalence, even if a small measure of false positives are occurring (Jorm et al., 2017; Ormel et al., 2022; Ormel & Emmelkamp, 2023). A recent dynamic modelling analysis from Australia provided evidence to suggest that the increasing prevalence poor mental health may be explained by an increase in the rate at which people with low or moderate psychological distress, are developing high or very high psychological distress (Skinner et al., 2022). Related work has highlighted that efforts to balance *supply* of psychological services with population *demand* has potentially overlooked subtler distributional aspects of treatment provision (Meadows et al., 2018). Across Australia, uneven allocation of mental health services has resulted in a mismatch between supply and demand. Medicare service use data has shown that the proportion of people utilising mental health services in urban locales exceeds 20%, whereas utilisation drops to less than 5% amongst people living outside of major urban areas. This is despite an even proportion of people reporting very high psychological distress across both regions. Moreover, people residing within areas of greater socioeconomic disadvantage are significantly more likely to report very high psychological distress, but significantly less likely to use mental health services than people residing in areas of lower socioeconomic disadvantage (Meadows et al., 2018). Thus, it remains possible that poorly targeted service allocation may be compromising the expected benefits of expanded service provision.

Additional research has gone further, indicating that while the *quantity* of available psychological services and treatments has increased, the *quality* has not (Andrews et al., 2000; Harris et al., 2015; Meadows & Bobevski, 2011). Collectively, this work identified that people commonly fail to seek psychological treatment, but when they do it is frequently inconsistent with best-practice clinical guidelines, or fails to meet their needs. More fundamentally, these intimations of a potential treatment “quality gap” are supported by evidence suggesting that the published literature overestimates both the short and long-term efficacy of extant treatments, that treatments are substantially less effective when deployed outside of controlled experimental conditions, that improvements in patient mental health do not always endure long-term, and that the effectiveness of treatment is significantly diminished amongst chronic-recurrent patients compared to non-recurrent patients (De Vries et al., 2018; Ormel et al., 2022; Ormel & Emmelkamp, 2023). In line with this, modelling of population mental health in Australia has demonstrated that 60% of the total burden of disease associated with mental disorders would remain, even under conditions assuming every patient was in receipt of best available psychological treatment (Andrews et al., 2004). Whilst this indicates that a substantial reduction in mental disorders may be gained under conditions where every individual receives optimal treatment, this finding also demonstrates that the majority of disease burden would remain – highlighting the inherent insufficiency of treatment alone. Despite this, in many contexts the allocation of resources towards treatment vastly outweighs those directed towards preventive health measures and health prevention research (Jorm, 2014; Jorm et al., 2017; Miller et al., 2011; Reavley & Jorm, 2014; Wykes et al., 2015a). That the majority of mental health resources are directed towards treatment, despite treatment alone being unable to affect the majority of disease burden, should be an unacceptable societal and political endpoint. Taken together, this evidence highlights the importance of increasing investment in prevention, and the necessity of targeting modifiable factors beyond the quantity and quality of treatment to prevent and reduce disease burden.

Adding to concerns around treatment quantity and quality, researchers in evolutionary psychology have elegantly argued that a failure to carefully delineate *symptoms* from *disease* may have led the fields of psychology and psychiatry to underappreciate the importance of environmental context as a source of arousal for extremes of emotion, such as anxiety and depression (Nesse, 2019). Importantly, this has coincided with a research zeitgeist of identifying the genetic and neurological correlates of mental illness (Border et al., 2019; Kingdon, 2020). Accordingly, public health messaging has tended to convey an impression that the aetiology of mental health problems is largely a product of pre-existing biological vulnerability, operating independently of our day-to-day living conditions (Haslam & Kvaale, 2015; Horwood & Augoustinos, 2022). Put simply, diagnostic systems and clinical approaches within the fields of psychology and psychiatry have tended to conflate the presentation of symptoms with manifestations of internal illness or disease (Nesse, 2023). It is possible this has led to thinking within these fields where symptoms have become reified as signs of inherent pathology, rather than proportional, evolutionarily patterned reactions to threatening situations or aversive environments. For example, the 'smoke detector principle' illustrates the utility of experiencing anxiety in response to ambiguous threats in our environment. Specifically, the *cost* of expressing a mistaken anxiety response, or 'false alarm', may be far lower than the potentially life threatening cost of not experiencing anxiety at all (Bergstrom & Meacham, 2016; Nesse, 2019). That is to say, an anxiety response does not necessarily mean a person meets the diagnostic criteria for an anxiety disorder, but that evolved systems that regulate protective responses are designed to be sensitive to threats around us. In turn, an anxiety response can be elicited by aspects of our modern environment that signal danger or cause for vigilance (Nesse, 2015, 2019; Nesse et al., 2016). Building upon this, evolutionary theorists have also proposed that our contemporary environment deviates with increasing speed from the conditions in which we adapted over millennia –

otherwise known as our environment of evolutionary adaptedness (EEA) (Hidaka, 2012). Within this "evolutionary mismatch", aspects of advanced modern societies may function as mental health risk factors due to their novelty and deviation from our evolutionary history (Gosrani et al., 2025; Hidaka, 2012).

The evolutionary mismatch hypothesis dovetails with Jorm's contention that the relative absence of incisive preventative measures in psychiatric health may be the principal reason why population mental health has not improved within a context of greater awareness, increased treatment availability, service expansion, and increased service utilisation (Jorm, 2014; Jorm et al., 2017). More specifically, attempts to improve population mental health may not have found ways to reduce or prevent exposure to proximal socioeconomic conditions in modern society that contribute to chronic stress arousal and increased risk of mental illness (Skinner et al., 2022). These include the experience of relative poverty, precarious employment, declining social capital, increasing economic inequality, loneliness, and social isolation (Allen et al., 2014; Braveman & Gottlieb, 2014; Compton & Shim, 2015; Eckersley, 2015; Kirkbride et al., 2024). As noted by Geoffrey Rose, if a sizeable or increasing proportion of a population remains exposed to disadvantaged socioeconomic conditions, then incidence will remain high, and prevalence will fail to decline. In such situations, he argued that shifting the entire distribution of risk exposure would produce the most efficacious outcomes at the population level. Explained simply and in the spirit of his own words, 'a small reduction in risk for the majority, may produce better health outcomes than a large reduction in risk for a few' (Rose, 1985; Rose & Day, 1990).

In summary, a downstream consequence of viewing symptoms as representative of specific pathologies *within* individuals, has been a comparative under-emphasis on conceptualising our day-to-day environment as comprising modifiable risk factors for mental health. It must be stressed that this is despite a *vast* literature examining the link between various socioeconomic factors and mental health (Kirkbride et al., 2024). Understanding how our environment, and changes to it, contributes to psychiatric conditions, allows for a broader and more nuanced understanding of risk factors contributing to contemporary mental health issues.

Social Determinants of Health

Within a particular society, patterns of health status can be compared within and between sub-populations, according to various aspects of socioeconomic position such as education, income, wealth, labour market participation, living conditions, and social class (Marmot et al., 2010). These factors are commonly characterised as "the conditions in which people are born, live, work, and age", and are shaped by cultural norms (Rice & Liamputtong, 2023), geography and demography (Diamond, 1998), and economic, social, health and environmental policy (Allen et al., 2014).

Social determinants of Health (SDH) models provide a framework to begin understanding why and how these factors influence health. More specifically, SDH models help to explain why some individuals may have a higher risk of disease, poorer outcomes following disease, or why the consequences of disease may have a greater impact upon the lives of some and not others. Very broadly, SDH models highlight the distribution of resources within and between populations as an important contributor to the prevalence, risk, and impact, of various health outcomes.

A range of SDH models have been conceptualised, differing in complexity, focus, included 'determinants', and the levels of society at which they operate (BARHII, 2023; Barton & Grant, 2006; Dahlgren & Whitehead, 2021; Frieden, 2010; Huynen et al., 2005; Labonte & Torgerson, 2005; World Health Organization, 2010). For example, the WHO Commission on Social Determinants of Health (CSDH) model posits that health outcomes are a product of multiple complex and dynamic interactions operating between the social, economic, and political context defining a country's key institutions, and the proximal 'material' conditions defining an individual's day to day existence. In practice, this model suggests that a country's socioeconomic and political mechanisms stratify populations according to structural characteristics such as income, wealth, education, occupation, social class, gender, and race or ethnicity. In turn, this stratification leads to individuals within a population experiencing varying levels of 'exposure' to a range of proximal risk or protective health factors. These include an individual's day to day material living circumstances, the daily psychosocial stressors they are exposed to, and the behavioural and biological factors, such as exercise, nutrition, and alcohol or tobacco consumption, that characterise their lives.

Importantly, prior research has shown that health outcomes differ in the extent to which they are sensitive to measures of socioeconomic status. Some health outcomes, such as breast and prostate cancer mortality, do not differ strongly across levels of income. In contrast, the prevalence of common physical conditions, such as heart-disease, diabetes, and obesity, tend to increase with relative socioeconomic disadvantage (Banks et al., 2006; Pickett &

Wilkinson, 2015). Mental health outcomes have shown strong sensitivity to various measures of socioeconomic status and position (Allen et al., 2014; Compton & Shim, 2015). Accordingly, the burden of mental ill health and illness is disproportionately carried by individuals with fewer financial resources, who tend to be of lower socioeconomic position or status.

This is not a recent finding. A large and ever-growing body of empirical research has repeatedly demonstrated that the prevalence of poor mental health consistently follows a steep social gradient (Kirkbride et al., 2024). Indeed, socioeconomic disadvantage represents one of the strongest risk factors for poor mental health. As far back as the early 1980's, Ronald Kessler and Paul Cleary remarked that "the excess of psychological distress in the lower social strata was one of the most consistent findings in psychiatric epidemiology" (Kessler & Cleary, 1980). This association has been observed across various measures of socioeconomic disadvantage. For example, poorer mental health is associated with the experience of relative or absolute poverty (Lorant et al., 2007; Lund et al., 2010), low income (Enticott et al., 2016; Isaacs et al., 2018; Muntaner et al., 2004), low wealth (Ettman et al., 2020; Kendall et al., 2019), lower socioeconomic status (Lemstra et al., 2008), experiencing or worrying about debt (Jenkins et al., 2008; Reading & Reynolds, 2001; Turunen & Hiilamo, 2014), and financial hardship or household financial strain (Butterworth, Olesen, et al., 2012; Domènech-Abella et al., 2021; Foulds et al., 2014; French & Vigne, 2019; Kiely et al., 2015; Selenko & Batinic, 2011). Additionally, factors related to labour market participation like unemployment (Bambra & Eikemo, 2008; Latif, 2015; Montgomery, 1999; Stuckler et al., 2009, 2011), job insecurity (Ferrie, 2002; Marmot et al., 2001), precarious or irregular employment (Benach & Muntaner, 2007), and involuntary job loss (Catalano et al., 2011), have also demonstrated robust associations with reduced mental health. Finally, even more distal factors, such as poor neighbourhood conditions (Halpern, 1995), economic recessions (Schrecker & Bambra, 2015), and higher national-level economic inequality (Kawachi & Subramanian, 2014; Layte, 2012; Layte & Whelan, 2014; Patel et al., 2018; Pickett & Wilkinson, 2010) are all associated with poorer mental health outcomes amongst those exposed to such conditions.

Each of these risk factors is associated with the day-to-day living conditions that contextualise our lives. Importantly, none of them are inevitable – therefore, they are modifiable and offer points of intervention (Allen et al., 2014). However, given their complex overlapping nature, it can be difficult to accurately model their unique influence on mental health. This multi-dimensionality means potential causal pathways are numerous, interconnected, cumulative and complex (Braveman & Gottlieb, 2014; Figueroa et al., 2020). Moreover, single measures of socioeconomic disadvantage can be insufficient at capturing this complexity accurately or precisely reflecting the degree of hardship experienced by an individual, leading to over or under-estimation of associations with health (Burns, 2015). Assessing socioeconomic disadvantage using a measure of financial hardship provides an approach that can circumvent some of these limitations.

Measuring Socioeconomic Disadvantage

Most commonly, poor living standards are inferred using *input-based* measures, which compare individual or household income against predefined absolute or relative poverty thresholds. Those who fall below the specified threshold are classified as socioeconomically disadvantaged. However, this thesis uses a measure of financial hardship to assess the experience of socioeconomic disadvantage – an *outcome-based* approach that evaluates the direct consequences of having insufficient financial resources. This approach identifies whether people have been excluded from minimally accepted standards of living by evaluating whether they have gone without goods or services that would be considered essential by their broader community (Bray, 2001; Butterworth, Olesen, et al., 2012; Butterworth & Crosier, 2005).

Comprehensively understanding the prevalence, distribution and correlates of financial hardship is a vital complement to prevailing research that has assessed living standards in Australia according to traditional relative poverty line measures. Moreover, it provides an essential foundation for further examination of important longitudinal relationships between financial hardship, including its trajectory over time with outcomes such as mental health.

Economic Context – The Past 25 Years

While the 21st century has been punctuated by a series of major global economic disruptions, Australia's economy has largely resisted these events and seen consistent year-on-year growth. Between 1991–92 and 2018–19, Australia's average annual real GDP growth rate was 3.1 per cent, and annual GDP per capita growth was 1.7%. To contextualise this, no other advanced economy achieved positive, uninterrupted GDP growth over 28 consecutive years. However, the COVID-19 pandemic abruptly ended this in 2020, with estimates suggesting the Australian economy was AUD 90 billion smaller in 2020-21 than it would have been under pre-pandemic growth trends (Ergas & Branigan, 2023).

However, this macroeconomic resilience has obscured pronounced changes to Australia's economy that have had wide-ranging implications for the living standards of households and individuals. This makes an assessment of the prevalence and distribution of poor living standards particularly pertinent.

Principally, the most topical and dramatic change has been the substantial rise in housing costs[11]. Over the past three decades, house prices in Australia have consistently outpaced both wage and CPI increases. Specifically, real housing prices have trebled, while real wages have increased by just 50% (Pawson et al., 2020, p. 53). Taking a one-year snapshot from December 2020 to December 2021 as an example, the weighted average increase in house prices across Australia's eight capital cities was 23.7% (Australian Bureau of Statistics, 2021c), while wages over the same period rose by just 2.4% (Australian Bureau of Statistics, 2024b).

The result of this has been a deepening wealth and income divide with respect to housing tenure. Analysis of data from the ABS Survey of Income and Housing (SIH) details that while before housing costs (BHC) poverty has decreased, after housing costs (AHC) poverty has increased – principally due to the rise in expense related to housing. While the relative poverty rate declined significantly from 9.6% in 2005–2006 to 8.0% in 2017–18, when controlling for housing costs, relative poverty rose slightly from 12.3% to 12.9% (Saunders et al., 2022a). Thus, while broadly distributed income growth has served to reduce the overall poverty rate within Australia, these gains have been nullified by rising housing costs, leading to increases in both poverty and inequality (Bradbury & Saunders, 2022; Saunders, 2017; Saunders et al., 2022b, 2022a). For many Australians, increases in income over the last three decades have been barely enough to offset rising housing costs (Saunders et al., 2022a). This is particularly evident when examining housing prices as a function of median gross disposable household income. In March of 2002, the median house price in Australia was 4.9 times the median gross disposable household income. However, in March of 2024, the median house price had increased to 8.6 times this amount (Australian Government, 2024, p. 136). Moreover, it has been estimated that in 1984, just 15.7% of mortgage holders spent more than 30% of disposable household income on housing costs; in 2024-25 this figure had risen to 44.5% (Australian Institute of Health and Welfare, 2025b). Morris (2023) has

[11] Morris (2023) has suggested that this is a product of prevailing housing policy, a neglect of social housing, and the resultant 'financialisation' of housing.

suggested that the rise in housing prices has been so dramatic in Australia that housing tenure is now a 'key determinant of one's wealth, disposable income, and capacity to lead a decent life'. Consequently, he has argued that approximately a third of Australian households may be locked out of home ownership for their entire lives.

Beyond housing costs, additional pressures have compounded household financial strain. Inflation exceeded 7 per cent in the September 2022 quarter (Tsiaplias & Wang, 2023), the Reserve Bank of Australia (RBA) cash rate[12] has surged from 0.1% in May of 2022 to 4.35% in November of 2023 (Australian Institute of Health and Welfare, 2025b), and economic growth has remained below pre-COVID historical levels. At the same time, steady increases in income and wealth inequality have occurred, particularly amongst those aged under 65 (Kaplan et al., 2018; Rebechi & Rohde, 2023; Saunders, 2017; Saunders et al., 2016, 2022a). Novel 'multidimensional' measures of inequality, that incorporate assessments of health and education, reveal an even steeper increasing disparity between rich and poor, while inequality of opportunity – defined as inequality due to factors outside of individual control (such as race, gender, and parental socioeconomic status) – has also risen over time (Rebechi & Rohde, 2023; Rohde & Guest, 2018).

It has been argued that increases in national GDP mean that the majority of households have experienced an improved standard of living – a 'la 'the rising tide that lifts all boats' – (Saunders et al., 2022a). However, the aforementioned changes to the Australian economy highlight that traditional measures of societal economic wellbeing (such as relative income poverty, or overall national GDP) may not fully capture the actual deprivation experienced by many residents in the population. Measures of financial hardship, which directly assess material deprivation, complement traditional measures of economic wellbeing, helping to provide a comprehensive picture of living standards when conducting social policy analysis.

Input-Based Measures of Poverty

Measures of poverty are commonly used to evaluate living standards and the prevalence of socioeconomic disadvantage within a society. However, despite broad recognition of poverty as centring around concepts of deprivation and impoverishment in both academic and public discourse, there remains no consensus on how best to objectively define or assess it (Bray,

[12] The RBA 'cash rate' is the benchmark interest rate that sets the lending rate between financial institutions in Australia. It influences all other interest rates, including mortgage and deposit rates, and has an indirect effect on inflation, employment and exchange rates (Reserve Bank of Australia, 2025a, 2025b).

2024; Callander et al., 2012). In turn, varying definitions and measures have emerged over more than a century of scholarly inquiry (Callander et al., 2012).

Importantly, these definitional and measurement differences go beyond philosophical or technical distinctions – they have a tangible effect on the outcome of any analysis. Different measures will identify different people as experiencing poverty, and at differing levels (Bray, 2024). Moreover, the observed associations with various outcomes such as physical or mental health will change depending on the specific measure of poverty employed (Foulds et al., 2014; Lahelma et al., 2006).

The majority of approaches use a measure of the financial *inputs* available to a household – such as income or wealth (Bray, 2024) – which are compared against specific absolute or relative poverty lines. Disadvantage is inferred when an individual or household falls below the set poverty line[13]. Hagenaars & de Vos, (1988) suggested that poverty measures can generally be classified into three main categories:

1. *Absolute Poverty* – defined normatively as having less than a specified absolute minimum of financial resources;
2. *Relative Poverty* – defined as having fewer economic resources than others within a given society;
3. *Subjective Poverty* – defined according to an individual's subjective perception of their financial situation[14].

Internationally, poverty is most commonly defined and measured using the relative approach, with the threshold for being poor set at having less than 50% of the median equivalised household income (Bray, 2001, 2024). In practice, this means the living standards of an individual or household are assessed in relation to the standards experienced by other people in the subject society. This 'relative' concept of poverty is long standing, with allusions to it found characterised within Adam Smith's oft cited 18th century quote on the necessity of

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[13] To enable robust comparisons between households of varying composition and size, it is standard practice to equivalise income or wealth data.

[14] Commonly measured by asking whether individuals perceive themselves as lacking sufficient economic resources, or by using a subjective assessment of their socioeconomic position, financial satisfaction, or sense of prosperity.

owning a 'linen shirt' lest one shame themselves in public[15]. Nonetheless, the majority of key contemporary studies assessing socioeconomic disadvantage within Australia have also identified those in poverty using a relative poverty line set at 50% of median equivalised household income (Callander et al., 2012; Saunders et al., 2022a).

In 2019-2020, an estimated 3.3 million Australians (13.4%) lived below the relative poverty line, as measured using the 50% threshold (Davidson et al., 2022). More recent analysis using HILDA survey data estimated that the proportion of Australian's living below the relative poverty line has ranged from 12.4% in 2001, to a low of 9.72% in 2014, before rising to 13.3% in 2022 (Bray, 2024).

Outcome-Based Measures of Poverty

In contrast to input-based measures, living standards can also be assessed using direct, outcome-based measures that capture the reported *consequences* of inadequate financial resources. This approach overcomes a key limitation of defining living standards solely in terms of income – low income is neither a necessary nor sufficient condition for poverty (Saunders & Adelman, 2006).

Broadly, the use of outcome-based measures is underpinned by the concept of poverty as exclusion – the inability to participate in the ordinary social, cultural, and everyday activities of one's community. Amartya Sen articulated this idea by arguing that poverty is fundamentally a lack of freedom, which he defined as "the deprivation of basic capabilities" needed to live a decent life (Sen, 1999). According to Sen, individuals constrained by limited opportunities are unable to achieve an adequate standard of living for themselves because they lack the freedom to fully engage, participate in, and function within society (Nussbaum & Sen, 1993). In defining poverty this way, Sen resolves the question of whether absolute or relative poverty is worse – highlighting that relative deprivation in terms of income, corresponds to absolute deprivation in terms of capabilities (Marmot, 2017).

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[15] Adam Smith's quote on the matter of public attire, in the context of relative deprivation, follows that: 'By necessaries I understand not only the commodities which are indispensably necessary for the support of life, but whatever the customs of the country renders it indecent for creditable people, even the lowest order, to be without. A linen shirt, for example, is, strictly speaking, not a necessary of life. .... But in the present times, through the greater part of Europe, a creditable day-labourer would be ashamed to appear in public without a linen shirt, the want of which would be supposed to denote that disgraceful degree of poverty which, it is presumed, nobody can well fall into, without extreme bad conduct.' (A. Smith, 1776/2002).

Outcome-based measures assess whether an individual or household has forgone necessities – such as food, shelter, medical care, and clothing – or experienced subminimal standards of living relative to the society they live within, due to insufficient economic resources (Mack & Lansley, 1985; Whelan, 1993; Whelan et al., 2001). This approach recognises that poverty goes beyond a paucity of financial resources – it encompasses an inability to access the items and activities deemed essential by most people in a given society. Thus, outcome-based measures emphasise the implicit link between a lack of financial resources and the downstream deprivation of everyday necessities. Importantly, this means the assessment of living standards is achieved by focusing on the actual experience of deprivation, rather than inferred as a function of available financial inputs (Bray, 2024).

This represents one of the key strengths of outcome-based measures – the impact of insufficient resources is assessed directly, without recourse to arbitrarily defined poverty lines. Moreover, income alone does not reflect the entirety of resources a household has to draw upon. A household's living standards reflect the product of various wealth assets, access to external financial support from family, friends or community networks, the use of credit or debt to manage liquidity ebbs and flows, and locational differences in living costs. Living standards may also reflect access to non-economic factors, such as the availability of people within a household to perform daily tasks, the health status of household members, and attitudes or behaviours commensurate with the efficient use of available resources (Butterworth & Crosier, 2005). Outcome-based measures implicitly account for the moderating role of these factors.

Furthermore, by directly asking respondents to identify constraints stemming from insufficient financial resources, outcome-based measures reduce bias related to taste, choice, need, and perceived significance (Butterworth & Crosier, 2005). These biases can be further mitigated by using multi-item scales to assess a range of deprivations, in order to sharpen discernment between actual hardship and personal choice. In contrast, input-based assessments of living standards have been criticised for misreporting income data, assuming income-sharing within households, and for the choice of equivalence scale used to adjust for differences in household composition (Corak, 2006; Ravallion, 2016; Saunders et al., 2022a) – all limitations that outcome-based measures help to overcome.

In practice, the imperfect relationship between financial hardship and income has been demonstrated in empirical analyses. For example, low-income households have been shown to report an absence of deprivation, while households above specified income-poverty thresholds may report significant levels of financial hardship (Whelan et al., 2001).

Extending this, several studies have shown that multi-item outcome-based assessments of material deprivation provide a superior estimation of the association between socioeconomic status and a range of outcomes, compared to traditional measures of income poverty, level of education, and employment status (Butterworth, Olesen, et al., 2012; Foulds et al., 2014; Lorant et al., 2007). Importantly, these associations are consistently observed across outcome-based measures, despite variation in the specific deprivations assessed.

For example, Butterworth et al. (2012) demonstrated that a seven item outcome-based assessment of financial hardship utilised by the Australian Bureau of Statistics (ABS) was a better predictor of depression in Australia than low income, unemployment, and neighbourhood-level disadvantage. When adjusting for hardship in multivariable models, these traditional indicators were no longer independently associated with depression. Similarly, Crowe & Butterworth, (2016), using a four-item measure, found that deprivation significantly mediated the relationship between unemployment and depression.

These findings dovetail with international research. Heflin and Iceland (2009) used a nine item scale to assess five hardship domains – including food, utilities, medical care, telephone access, and housing – and found that material hardship mediated much of the relationship between poverty and depression in a sample of US mothers with young children. Moreover, Lorant et al. (2007) and Foulds et al. (2014)[16] both demonstrated that composite indices of deprivation were more strongly associated with depression and psychological distress than income or employment status in samples from Belgium and New Zealand respectively.

Furthermore, experiencing multiple deprivations has demonstrated a dose-response relationship with mental health, with the odds of depression almost doubling compared to experiencing a single deprivation (Butterworth, Olesen, et al., 2012). Research using a similar seven-item measure across ten waves of the Korean Welfare Panel Study, showed that both the experience of severe financial hardship over two consecutive years, and increased

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[16] Foulds et al. (2014) used the Economic Living Standards Index) comprising 25 questions assessing asset ownership, economising behaviour, self-perception of economic status and experiences of social exclusion due to insufficient financial resources.

financial hardship over the previous year, were associated with significantly increased odds of depression (Choi et al., 2023).

With respect to temporality, there is consistent evidence highlighting that the detrimental effects to mental health of deprivation occur with relative immediacy (Butterworth, Olesen, et al., 2012; Kiely et al., 2015; Lahelma et al., 2006; Lorant et al., 2007; Mirowsky & Ross, 2001; Weich & Lewis, 1998). Moreover, experiencing deprivation is not only associated with an increased risk of onset for major depression, but also with an enduring elevated risk of mental health problems, even after deprivation has resolved (Skapinakis et al., 2006). Further work by Kiely et al. (2015) demonstrated that this relationship is exacerbated where the experience of deprivation re-occurs. Given this, the experience of financial hardship may play a causal role in not just precipitating the onset of mental illness, but in maintaining its existence on individuals already suffering (Butterworth, Olesen, et al., 2012).

More broadly, deprivation experience has been associated with elevation in various markers of inflammation – including IL6, CRP, and fibrinogen – (Surachman et al., 2023), obesity (Conklin et al., 2013), reduced medication adherence (Marshall & Tucker-Seeley, 2018), smaller left and right hippocampal amygdala volumes (Butterworth, Cherbuin, et al., 2012) and an increased likelihood of reporting low self-rated health, even after controlling for demographic characteristics, socioeconomic factors, and psychological distress (Tucker-Seeley et al., 2013). Finally, work by Bentley et al. (2023) has highlighted the deleterious impact to both mental and cardiovascular health of being unable to warm one's home due to a shortage of money.

Taken together, this evidence highlights the empirical advantages of outcome-based measures in capturing living standards and the experience of impoverishment. As a result, outcome-based measures have found use as both a complement and alternative to assessments of income-based poverty in social policy analysis (Bray, 2001).

Financial Hardship

The outcome-based measure used within this thesis is a seven-item scale constructed from a broader set of questions developed by the Australian Bureau of Statistics (ABS). These items were informed by prior research examining living standards within Australia, and formally introduced in the 1998-99 Household Expenditure Survey (Bray, 2001). The seven items collectively evaluate whether a household could not afford to pay for a range of socially perceived essential goods and services – such as utilities, housing expenses, heating costs, or food – along with whether they have been compelled to pawn belongings, or seek financial help from friends, family, or welfare organisations as a result of inadequate financial resources.

Butterworth and Crosier (2005) used the term *financial hardship* to define this specific collection of items, in order to emphasise the link between limited financial resources and the experience of hardship. Throughout this thesis, this term will be used when referring to this specific seven-item outcome scale.

Conceptually, the items comprising this financial hardship scale are similar to the dimension of deprivation Whelan and colleagues defined as *basic lifestyle deprivation* (Whelan, 1993; Whelan et al., 2001). They also align with Beverly's (2001) conception of *material hardship* – which she defined with respect to inadequate consumption of very basic goods and services – and *financial hardship* – having difficulty paying rent/mortgage or utilities. Importantly, this seven-item financial hardship measure is focused on capturing the objective indicators of material need, as opposed to the social dimensions of exclusion, or the subjective elements of financial satisfaction or perceived prosperity (Butterworth & Crosier, 2005).

Furthermore, factor analysis has shown that these seven items reflect two correlated sub-dimensions. Using data from the 1998–99 Household Expenditure Survey, Bray (2001) identified a robust three-factor solution. Three items pertaining to not being able to pay utilities, housing costs, and asking for financial help from friends and family, loaded onto a single factor. Bray termed this factor "cashflow problems" given it reflected household budgetary challenges, as opposed to direct deprivation. The remaining four items pertaining to pawning items, being unable to heat one's home, going without meals, and asking for help from welfare/community organisations loaded onto a second factor. Bray termed this "hardship", given it represented deprivation arising due to limited financial resources. A third factor, *missing out*, consisted of six items reflecting constraints on lifestyle and leisure; these items do not contribute to the seven-item measure of interest here. Nonetheless, subsequent work by Kiely et al. (2015) demonstrated that both dimensions of the two-factor solution (cashflow problems and deprivation) were significantly associated with poor mental health. Related analyses have also shown that a unidimensional model provides an adequate fit for these seven items (Butterworth & Crosier, 2005).

This specific seven-item measure of financial hardship has been widely used within Australian research over the past two decades to examine its relationship with various health outcomes (Butterworth et al., 2009; Butterworth, Olesen, et al., 2012; Crowe et al., 2016; Kiely et al., 2015). Using data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, Bray (2024) estimated that in 2022 approximately 18.2% of the Australian population aged 15 years and over had experienced at least one of the seven hardship items. Notably, the majority of these individuals (14.6%) were not classified as experiencing relative income poverty – highlighting the aforementioned imperfect relationship between material deprivation and income.

In particular, studies have repeatedly highlighted that this measure of financial hardship has a strong and independent relationship with mental health, and that it mediates the relationship between traditional measures of social position and mental health (Butterworth et al., 2009; Butterworth, Olesen, et al., 2012). Extending upon this, work by Kiely et al. (2015) showed that in both between and within-person analyses, current financial hardship – rather than past hardship – shared the strongest association with concurrent reductions in mental health. Similarly, Crowe et al. (2016) applied the same seven-item measure and found that financial hardship significantly attenuated the association between unemployment and poor mental health.

A Brief History of the Deprivation Approach to Assessing Living Standards

The systematic use of outcome, or deprivation approaches to assessing living standards was pioneered by Townsend (1979, 1987). Townsend's approach to identifying and measuring deprivation sought to characterise the *actual* living conditions associated with poverty, rather than just defining poverty as a function of income or wealth. In this context, Townsend defined deprivation as, 'a state of observable and demonstrable disadvantage relative to the local community or the wider society or nation to which an individual, family or group belongs' (Townsend, 1987: pg. 125). Townsend operationalised this concept using a multidimensional measure of poverty comprising twelve indicators to assess 'styles of living'. This included domains pertaining to food adequacy (e.g., whether the household could afford fresh meat or a cooked breakfast), household amenities (e.g., possession of a refrigerator or indoor toilet), and leisure activities (e.g., the capacity to take a holiday). Households responded by affirming whether they possessed the item or undertook the activity. Households that recorded going without six or more indicators were classified as having experienced deprivation. Notably, Townsend considered the primary objective of his deprivation analysis to be in establishing where an objective poverty line should be set – as opposed to identifying which households were experiencing deprived living conditions. Townsend assumed the existence of a threshold that would mark a dramatic decline in living standards, characterised by a large proportion of households moving from a point of income adequacy to income poverty. It was this point, where the incidence of deprivation increased dramatically, that Townsend suggested a poverty line should be set (Bray, 2001).

Townsend's approach was subsequently refined by Mack and Lansley (1985) in two key ways. Firstly, they asked respondents to describe whether they considered each item included in their deprivation scale as 'essential', and whether households should be able to afford them. Mack and Lansley then used this information to determine which items should continue to be included in their deprivation scale. Secondly, they also sought to account for the bias associated with personal taste, by asking respondents whether they went without an item because they could not afford it. Consequently, households were only classified as being deprived of an item if its absence was due to financial constraints. Like Townsend, Mack and Lansley scored their deprivation scale by simply summing the number of specific deprivations each household reported. However, in contrast to Townsend, who sought to assess deprivation as a means of defining a specific income poverty line, Mack and Lansley simply relied on the incidence of deprivation itself as a measure of poverty (Bray, 2001).

Subsequent work by Nolan and Whelan (1996) applied a similar approach to Mack and Lansley (1985). While they maintained Mack and Lansley's concept of 'enforced lack' – whereby deprivation was only recorded in instances where items were lacking due to insufficient financial resources – they did not systematically exclude items from their scale on the basis of most households not having it or viewing it as inessential. Moreover, Nolan and Whelan identified three distinct dimensions of deprivation using factor analysis – *basic lifestyle deprivation*, which included lack of basic food, inadequate clothing, and insufficient heating; *secondary deprivation*, which broadly covered lifestyle items and activities such as leisure, a car, telephone, and central heating; and *housing deprivation*, which assessed the availability of a bath or a shower, an indoor toilet, a refrigerator, a colour television, and a washing machine. A key difference to Nolan and Whelan's approach was defining poverty in terms of available financial resources *and* outcomes. In practice, this helped to delineate households with incomes below a specific income poverty line, from those also experiencing deprivation.

Other approaches to assessing deprivation have explored weighting items to account for the number of people in the community who possess the item, and who identify the item as being essential (Desai & Shah, 1988). Similar work has suggested placing greater weight on the deprivation of items that were possessed by larger proportions of the population *and* of those considered to be a necessity by larger proportions of the population (Bray, 2001).

Summary

Along with being a leading contributor to burden of disease estimates, research has shown that the prevalence of mental disorders in high-income developed countries, including Australia, has remained stable or even increased over the past thirty years. This is despite improvements to funding towards mental health, substantial expansion of mental health treatment, and evidence of significant increases in treatment utilisation. A range of research has been conducted attempting to reconcile this apparent "treatment-prevalence paradox". In light of this, it is possible that attention should be turned towards a broader range of factors contributing to persistent and rising rates of mental illness. Indeed, a highly robust body of evidence has accumulated for decades demonstrating the link between socioeconomic factors and mental health. However, it is possible that the relative focus upon the genetic and biological correlates of mental illness has come at the cost of acting upon the recommendations of this work. As a result, the socioeconomic conditions associated with poor mental health may have remained under-addressed, and therefore persisted for a sizeable proportion of the population. Nonetheless, further refining our understanding of the association between mental health and socioeconomic disadvantage may be crucial in reducing the burden of disease that is associated with modifiable socioeconomic risk factors. Financial hardship is an outcome-based measure of socioeconomic disadvantage that directly assesses the impact of insufficient financial resources. In several studies it has been demonstrated to provide a superior estimation of the relationship between socioeconomic disadvantage and mental health, compared to measures of income, employment status, and area-level disadvantage. This thesis will explore the relationship between financial hardship and mental health through a systematic review of the international evidence and three empirical investigations. The ensuing section outlines this body of work and how it will address key gaps, and extend upon the prevailing literature.

Thesis Outline

Given the aforementioned benefits of assessing socioeconomic disadvantage with respect to financial hardship, and the noted gaps in empirical work in this area to date, the overall aim of this thesis is to quantify the association of financial hardship with mental health using longitudinal data and longitudinal analytic techniques.

Four empirical chapters designed to quantify these associations are proposed below:

1. *The longitudinal relationship between financial hardship and mental health - A systematic review of the evidence*
2. *The Prevalence and Correlates of Financial Hardship in Australia – 2001 to 2023*
3. *Assessing Temporality in the Bi-Directional Relationship Between Financial Hardship and Mental Health: A Random-Intercept Cross-Lagged Panel Analysis of HILDA Data*
4. *The Association Between Long-term Profiles of Financial Hardship Experience, Latent Financial Hardship State Transitions, and Mental Health*

Each of these empirical chapters will take a longitudinal perspective to explore the relationship between financial hardship and mental health over time.

Empirical Chapter 1

There exists an abundance of evidence demonstrating the link between socioeconomic disadvantage and a wide range of health outcomes. Mental health is one such outcome – upon which, a clearly defined social gradient operates whereby those of lesser material and financial means evidence substantially greater rates of poor mental health. This relationship is highly robust. It has been confirmed across various measures of socioeconomic disadvantage, within an array of novel research papers, systematic reviews and meta-analyses conducted over the past three decades. Despite this, a comprehensive and systematic assessment of the specific relationship between financial hardship and mental health remains absent from the peer-reviewed literature. As noted earlier, financial hardship measures *directly* evaluate the consequences of lacking adequate financial resources – a feature which both distinguishes them from, and confers several advantages over, more commonly utilised measures of socioeconomic disadvantage. Given this, the first empirical chapter of this thesis will attempt to address this gap in the literature, with the express aim of synthesising prevailing international evidence to better understand the longitudinal relationship between financial hardship and common mental health conditions. Importantly, this review will focus on studies that use longitudinal data, with repeated measures of the same individuals over time, with the goal of gaining specific insight into the temporal dynamics of this relationship. Specifically, this chapter will aim to:

1. *Identify constructs and terms that have been used to define and measure financial hardship;*
2. *Evaluate the overall longitudinal relationship between financial hardship and common mental health conditions;*
3. *Identify methodological, analytic, and key participant characteristics that may explain heterogeneity in this relationship;*
4. *Critically appraise the quality of the prevailing international evidence base.*

More broadly, the results of this systematic review will be used to inform the ensuing empirical chapters, in terms of appropriate analytic techniques and outstanding gaps in the literature.

Empirical Chapter 2

Accurate, present-day epidemiological estimates of financial hardship prevalence in Australia are fundamental to quantifying its population impact. Understanding how financial hardship is distributed across the population and the strength of its association with key sociodemographic correlates and health outcomes is vital for identifying who is impacted, and what factors increase or decrease one's risk of exposure. Collectively, this insight is an essential foundation for conducting valid, robust, and interpretable models estimating the association between financial hardship and mental health.

Moreover, quantifying the impact of financial hardship complements more commonly used measures of socioeconomic disadvantage like relative poverty lines, by providing a more comprehensive understanding of living standards and economic wellbeing across the population. In line with this, it is arguable that economic changes in Australia over the past 25 years have altered the relationship between income and living standards. Increased concentrations of income and wealth in the upper socioeconomic strata since the 2008 financial crisis and again following the COVID-19 pandemic, along with significant increases in housing costs, stalled wage growth, increasingly widespread forms of precarious employment, and greater levels of household debt, have likely impacted people's ability to afford basic necessities. Given this, more commonly utilised measures of societal and individual economic wellbeing, such as national GDP or relative income poverty may be insufficient at capturing the absolute levels of deprivation currently being experienced by many Australian households.

Therefore, this chapter will aim to:

1. *Estimate the prevalence of financial hardship in Australia between 2001 and 2023;*
2. *Quantify the strength of the association between financial hardship and key sociodemographic, health, and mental health factors;*
3. *Evaluate how the strength of the relationship between both sex, and age with financial hardship, has changed over time.*

Empirical Chapter 3

The previous chapter is designed to provide precise population-average estimates of the association between financial hardship and mental health between 2001 and 2023, while controlling for key sociodemographic correlates. The third empirical study of this thesis is designed to extend the findings of the second empirical study – specifically by examining aspects of temporality, directionality, and within-person change in the relationship between financial hardship and mental health.

The focus on temporality and directionality is particularly salient. The question of whether socioeconomic disadvantage precedes poor health, or whether poor health precedes socioeconomic disadvantage, has occupied substantial research interest for decades (Kröger et al., 2015; Warren, 2009). Two hypotheses have been proposed to explain each directional pathway in this relationship – the *social causation* hypothesis and the *health selection* hypothesis (Goldman, 1994). The social causation hypothesis stipulates that exposure to adverse socioeconomic conditions raises one's risk of poor health (Dohrenwend et al., 1992; Hudson, 2005; Kröger et al., 2015; Mossakowski, 2014). Conversely, the health selection hypothesis holds that it is poor health that leads to impoverishment (Dohrenwend et al., 1992; Mossakowski, 2014; West, 1991). However, evidence confirming the directionality and temporality of this bi-directional relationship remains inconclusive, varying with different measures of socioeconomic disadvantage, the focal health outcome assessed, and the employed research design. In this same spirit, the temporality and relative strength of each directional pathway operating between financial hardship and mental health also remains uncertain.

Moreover, a key limitation common to many studies striving to disentangle the role of causation and selection effects is the conflation of between- and within-person differences. Thus, in order to accurately estimate each of these pathways, one must employ methods that disaggregate stable between-person differences from more transient within-person changes.

Thus, by using random-intercept cross-lagged panel models, the third empirical chapter aims to address this research gap by:

1. *Examining the temporal ordering between financial hardship and mental health;*
2. *Presenting estimates of within-person effects for each directional pathway;*
3. *Quantifying the relative strength of the within and between-person components operating in this relationship.*

Empirical Chapter 4

This chapter will extend upon the previous chapter – which focused on temporal and directional aspects of the longitudinal relationship between financial hardship and mental health – by examining profiles of long-term financial hardship experience and how these relate to mental health.

Life-course approaches in epidemiology enable insight to be gained on how the long-term experience of a specific risk-factor influences the development of a particular health outcome. To date, it is unclear how financial hardship is typically experienced across the life-course, whether there exist distinct long-term profiles of financial hardship experience, and how these may relate to mental health. Moreover, the majority of studies assessing the impact of financial hardship on mental health have examined the aggregate relationship across entire populations, or with respect to sex and age. However, identifying whether there exist heterogenous subgroups with respect to the timing, accumulation, and sequencing of financial hardship experience, may illuminate factors associated with divergence in mental health outcomes.

The fourth empirical study will therefore aim to examine the extent to which there exist distinct profiles of financial hardship experience and assess their relationship with mental health. In particular, this study will use social sequence analysis to describe and visualise the overall experience of financial hardship, with respect to the order and timing of cashflow problems and deprivation. Latent transition analysis will be used to explore whether meaningful latent financial hardship states exist and, along with mixed-effects logistic regression models, to gain a more nuanced understanding of the impact on mental health of state membership and transitions between them.

Data Sources

Chapter one of this thesis is a systematic review and therefore uses data extracted from the set of papers that met eligibility criteria. The analyses conducted in chapters two, three, and four of this thesis use data from twenty-three waves (2001-2023) of the Household, Income and Labour Dynamics in Australia (HILDA) survey. To avoid overlap, detailed information on the background, history, conception, and implementation of the HILDA survey is provided below. Information pertaining to the specific sample, measures, and analyses used for each study can be found under the methods section of each chapter.

The HILDA Survey

The HILDA Survey is an ongoing, annual household panel survey that commenced in 2001. It is managed by the Melbourne Institute of Applied Economic and Social Research and funded by the Australian Government Department of Social Services. The HILDA Survey was established to address the lack of long-running longitudinal survey data in Australia, and to support a growing emphasis within the Australian Government throughout the 1990's on the need for evidence-based policy (Watson & Wooden, 2012; Wooden & Watson, 2007). Thus, the HILDA Survey was explicitly designed to collect an array of data capable of guiding current and future policy developments, as opposed to providing information for evaluating specific policy initiatives (Watson & Wooden, 2012).

The HILDA Survey is one of the few large, well-established, nationally representative household panel studies conducted in the world. Its design draws substantial influence from similar well-established panel studies, particularly the German Socio-Economic Panel (GSEOP), the Canadian Survey of Labour and Income Dynamics (SLID), and the British Household Panel Survey (BHPS)(Watson & Wooden, 2012). The HILDA Survey contains a sample that is broadly representative of the Australian national population residing within private households, with the exception of individuals living in very remote parts of the country who have been under-sampled[17] (Watson & Wooden, 2002).

The HILDA Survey commenced with a large, multi-stage national probability sample of Australian households living in private dwellings. Details on how households were defined, how initial sampling was conducted, and how in-scope wave 1 households were identified can be found in Wooden & Watson (2007) and Watson & Wooden (2012). The wave 1 sample comprised 13,969 individuals aged 15 years and older from 15,127 total eligible household members – this provided a household response rate of 65.7 percent and an effective individual response rate of 61 percent (Wooden & Watson, 2007). Additionally, a population-wide sample top-up was completed in wave 11 to maintain the cross-sectional representativeness of the HILDA panel in accord with demographic changes since the survey's inception in 2001 (e.g., the underrepresentation of recent immigrant arrivals) (Watson, 2011; Wooden et al., 2024). These households form the basis of the HILDA panel, and the survey is designed to follow these members indefinitely.

However, the sample of participants interviewed at each wave is dynamic, given the panel is subject to attrition *and* expansion. Specifically, the design of HILDA allows for the automatic extension of the baseline sample, by incorporating new members of existing households into the survey frame (Watson & Wooden, 2012). Over the life of the survey, the original sample has been extended to include over 7,000 new households.

Overall, the HILDA Survey has achieved consistently high annual re-interview rates (86.9 percent - 97.0 percent) – increasing steadily from the initial years of study to rates in excess of 95 percent. Attrition is mainly due to refusal, death, and failure to make contact. It has been highest amongst participants who are younger, single, unemployed, working in low-skilled occupations, of non-English speaking background, or of Aboriginal or Torres Strait Islander origin (Summerfield et al., 2023; Wooden et al., 2024).

Since inception in 2001, the HILDA survey has been conducted annually and to date, comprises twenty-four waves of data. Each wave of data includes a set of person-level weights that enable analysis of the sample to reflect ABS population benchmarks.

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[17] This includes both indigenous and non-indigenous Australians.

The key instruments included in the HILDA Survey are administered via a combination of personal interviews and self-completion questionnaires. The personal interview component includes both core topics and a series of rotating topics. Core topics are included in the survey every year. They are designed to collect socio-demographic data on aspects of household composition, education, labour force participation, employment history, income, questions related to family formation and relationships, and general questions about living in Australia. Rotating topics are asked on a four-year cycle. These are designed to complement information gained from the annual core topics, with data on household wealth, family formation, retirement, health, education, and skills.

The self-completion questionnaires collect information on personal characteristics and attitudes, including relationship satisfaction, social interaction and support, general health, mental health and well-being, life events, lifestyle behaviours and outcomes related to smoking, exercise, and alcohol consumption, along with experiences related to financial prosperity, stress, and hardship. The self-completion questionnaires enable the survey to include more content without making the interview component too long, while also providing a format to engage topics respondents may find uncomfortable answering in the presence of an interviewer.

Given the broad and comprehensive range of topics assessed within the HILDA survey, it is particularly well suited to exploring research questions at the intersection of socioeconomics and health. Ironically, initial conceptions of HILDA did not comprise the inclusion of instruments to assess mental health. However, the addition of these measures has contributed substantially towards improving our understanding of population health in Australia. Firstly, it has addressed the nations lack of representative *longitudinal* data on mental health. Secondly, in concert with the HILDA survey's detailed economic measures, it has enabled research into the socioeconomic causes and consequences of mental health – akin to that explored within this thesis. Now, over twenty years on from its inception, estimates have shown that close to a fifth of all published articles using HILDA survey data have had a substantial focus on mental health. Moreover, the proportion of papers using HILDA survey data to examine mental health is progressively increasing each year (Butterworth et al., 2021; Butterworth & Crosier, 2004).

The HILDA Survey has ethical clearance from the Faculty of Business and Economics Human Research Ethics Committee at the University of Melbourne (Melbourne, Australia).

Measures

Financial Hardship, Cashflow Problems, Deprivation

The focal exposure variable in this thesis is financial hardship. It is assessed by asking respondents whether they have experienced any of the following indicators in the past 12 months due to a shortage of money:

1. *Could not pay electricity, gas, or telephone bills on time.*
2. *Asked for financial help from friends or family.*
3. *Could not pay mortgage or rent on time.*
4. *Pawned or sold something.*
5. *Was unable to heat home.*
6. *Went without meals.*
7. *Asked for help from welfare/community organisations.*

In chapters 3 and 5 responses to these seven items are summed and then categorised into a binary, yes/no variable, such that participants endorsing at least one item are classified as experiencing financial hardship. In chapter 4 responses are summed into a continuous score from 0-7, such that 0 is no financial hardship and 7 is maximum financial hardship.

Additionally, factor analysis has demonstrated that these seven items load onto two correlated subdimensions of hardship. One reflecting *cashflow problems* (items 1-3), and another reflective of *deprivation* (items 4-7) (Bray, 2001; Butterworth & Crosier, 2005; Kiely et al., 2015). Again, two binary, yes/no variables are constructed to classify participants endorsing at least one item of cashflow problems and/or deprivation.

Time Block

A ‘time block’ variable is used to categorise the 23 years of available data into four discrete periods: 2001-2006, 2007-2012, 2013-2018, and 2019-2023. These intervals were chosen to be roughly equal in length, and to enable an assessment of whether changes in the odds of experiencing hardship and/or poor mental health were evident over time.

Sex, Age, Birth Cohort

Sex is assessed as a binary male/female variable, as assigned at birth. Age is defined according to completed years (at most recent birthday) as of the date of interview. Accordingly, it is measured at each wave and is a time-varying variable. For analyses throughout this thesis, age is categorised into seven groups: 15-19, 20-29, 30-39, 40-49, 50-59, 60-69, and 70+. Birth cohorts are categorised as 1900-1929, 1930-1949, 1950-1969, 1970-1989, and 1990-2009.

Education and Employment

Education level at each wave is grouped into five categories: Year 11 or below, Year 12, Diploma/Vocational, Undergraduate, and Postgraduate. The Year 11 or below category includes individuals whose highest level of completed education at each wave was Year 11. Similarly, individuals whose highest level of completed education at each wave was Year 12 were grouped accordingly. The Diploma/Vocational category included individuals whose highest level of completed education qualification at each wave was either a diploma, an advanced diploma, or a TAFE Certificate III or IV. The Undergraduate category included individuals whose highest level of completed education was either a bachelor's or honour's degree, or a graduate diploma or certificate. Finally, the Postgraduate level comprised individuals whose highest level of education at each wave was either a master's degree or doctorate.

Employment status is categorised as either full-time, part-time, unemployed, or not in the labour force. The full-time category includes all individuals who indicate their work hours to be unknown. The number of individuals reporting unknown work hours each year was less than thirty, thus they were not expected to bias results associated with the full-time category.

Income

All income values were adjusted to December 2023 dollars using the weighted average Consumer Price Index (CPI) value in Australia for this period (Australian Bureau of Statistics, 2024a). Income is measured at the household level and equivalised using the OECD-modified scale to adjust for variation in household size and composition. This scale assigns a weight of 1 for the first adult in the household, 0.5 for each additional household member aged 14 or above, and 0.3 for each additional household member under 14. Total household income is then divided by this equivalence factor, and the resulting value assigned equally to all household members. Income quintiles are coded in accord with these values.

Area-level Socioeconomic Disadvantage

Area-level socioeconomic disadvantage is measured using the Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD)

(Australian Bureau of Statistics, 2021b). The IRSAD is one of several SEIFA indexes designed by the Australian Bureau of Statistics (ABS) to summarise the social and economic conditions of people and households across different areas of Australia[18]. These areas are demarcated according to census districts defined in 2001.

The ABS defines socio-economic advantage and disadvantage in terms of 'people's access to material and social resources, and their ability to participate in society' (Australian Bureau of Statistics, 2021a). Each SEIFA index combines various indicators of socioeconomic status to assess area-level disadvantage in accord with this. For example, the IRSAD index includes measures such as, the percentage of people with a stated household income between $1 and $25,999 per year, the percentage of employed people classified as 'labourers', the percentage of occupied private dwellings with four or more bedrooms, the percentage people aged 15 years and over whose highest level of education is Year 11 or lower, and the percentage of people (in the labour force) who are unemployed[19].

The IRSAD ranks areas on a continuum from most disadvantaged to most advantaged. Higher scores on this index indicate an area containing a relatively high incidence of advantage (households with high incomes and many people with tertiary qualifications and high skill occupations) and a relatively low incidence of disadvantage (households with low incomes and many people without tertiary qualifications and low skill occupations). The ABS stresses that this index is assigned to areas, not individuals. Accordingly, it is indicative of the collective socio-economic characteristics of the people living in an area.

In the present analysis IRSAD scores at each wave are categorised into quintiles, consistent with the approach adopted for household-level income. Quintile 1 represents areas of most disadvantage, while quintile 5 represents areas of most advantage.

Physical and Mental Health

Physical and mental health are measured using the *Physical Functioning* and *Mental Health (MHI-5)* subscales of the SF-36 Health Survey.

The SF-36 is a multipurpose, multidimensional, 36-item health survey originally developed for use in the Medical Outcomes Study (MOS). It was designed to provide a concise, yet

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[18] Complementing the IRSAD, the ABS also assesses SEIFA using the Index of Relative Socio-economic Disadvantage (IRSD), the Index of Economic Resources (IER), and the Index of Education and Occupation (IEO).
[19] The full list of variables used to construct the current (2021) SEIFA Index of Relative Socio-Economic Advantage and Disadvantage is provided in Appendix B.1.

comprehensive assessment of health status across eight key domains. These include physical functioning, bodily pain, social functioning, mental health, vitality, general perceptions of health, and role limitations due to emotional and physical health problems (Ware & Sherbourne, 1992).

Physical Health is measured using the *Physical Functioning* subscale of the SF-36 Health Survey. This subscale aims to capture distinct aspects of physical functioning across a range of minor to severe physical limitations. The Physical Functioning subscale consists of 10 items which collectively evaluate the degree to which physical health has restricted an individual's ability to undertake specific activities over the preceding four weeks. Each item is answered across a three-level response continuum. Respondents scores across the 10 items are recoded (where required) summed and then scaled from 0 to 100, with higher scores indicating better physical functioning (Ware et al., 1993). For this analysis, physical functioning scores were categorised into deciles – higher deciles indicated better physical functioning. The ten items, along with the three response options, are listed in Appendix B.2.

Mental Health is assessed using the five item *Mental Health (MHI-5)* subscale of the SF-36 Health Survey. The MHI-5 is designed to assess general mental health over the preceding four weeks by examining symptoms of psychological distress and well-being, including anxiety, depression, and happiness (Ware, 1987, 2000; Ware & Sherbourne, 1992). Respondents answer each item over a 6-point Likert scale. Scores on each item are recoded (where necessary), summed and then transformed to a scale ranging from 0 to 100. Higher scores are indicative of better mental health (Ware et al., 1993). As with the Physical Functioning subscale, MHI-5 scores were categorised into deciles – higher deciles indicated better mental health. The five items contained in this scale, along with the response options are detailed in Appendix B.3.

The *Physical Functioning* ($\alpha = 0.93$) and *Mental Health* ($\alpha = 0.90$) subscales of the SF-36 both demonstrated excellent internal consistency in the original Medical Outcomes Study data (RAND Corporation, n.d.). Additionally, the internal consistency of both subscales has been tested using HILDA data, which also demonstrated excellent reliability scores. Specifically, Cronbach's alpha ranged from 0.82 for the *Mental Health* subscale to 0.93 for the *Physical Functioning* subscale (Butterworth & Crosier, 2004). Both subscales have also demonstrated strong construct validity as accurate indicators of physical and mental health (respectively), and an ability to distinguish groups differing in severity of physical and mental illness (Mchorney et al., 1993; McHorney et al., 1994).

Residing with Parent

A binary (Yes/No) variable is used to indicate whether an individual reported living in the same household as their parents. This was derived from two variables indicating the co-residence of a father or mother in the household.

Chapter 2 - The Longitudinal Relationship between Financial Hardship and Mental Health - A Systematic Review of the Evidence

Abstract

Background: A compelling body of evidence has accumulated in recent years highlighting the association between various socioeconomic factors and a wide range of mental health outcomes. This includes financial hardship – described by Mack & Lansley (1985) as "an enforced lack of socially perceived necessities" – the experience of which has demonstrated a strong negative effect on mental health. To date however, no systematic review of the evidence assessing the longitudinal relationship between financial hardship and mental health has been undertaken.

Aims: The aim of this review is to better understand the longitudinal relationship between financial hardship and mental health, to critically appraise the quality of existing evidence, and to identify factors that may explain heterogeneity in this association.

Methods: Scopus, PsycINFO, MEDLINE, Embase, PubMed were searched from inception to July, 2023 and yielded a total of 8,672 records. Following de-duplication, abstract and full-text screening, 94 studies met inclusion criteria. Included studies were published between 1987 and 2023, and spanned 26 countries. Study quality was assessed using items from both the Joanna Briggs Institute Checklist for Cross-Sectional Studies, and the Joanna Briggs Institute Checklist for Cohort Studies.

Results: Overall, the quality of included studies was high, sharing an average rating of 80 percent. The reviewed literature overwhelmingly demonstrated a positive longitudinal association between financial hardship experience and poorer mental health. Despite a diversity of locations, study designs, analytic techniques, modelled confounders, and measures of mental health and financial hardship, 101 of 116 multivariate assessments demonstrated a positive relationship between financial hardship and poorer mental health, particularly depression.

Conclusion: This body of evidence highlights a clear association between financial hardship and poorer mental health, reinforcing the necessity of intervention that can mitigate the experience of deprivation due to lack of financial resources, and in turn promote mental health.

Introduction

A compelling body of evidence has accumulated in recent years highlighting the association between various socioeconomic conditions and a wide range of health outcomes (Kirkbride et al., 2024). This work has complemented our existing understanding of health – as being a product of proximal individual factors such as genetics, biology, lifestyle, nutrition, and access to medical care – by incorporating insight into the additional, broad influence exerted by more distal social, economic, and political factors (Braveman & Gottlieb, 2014). While it is well established that diseases and illness commonly have biological causes, their distribution within and between populations can be explained via various measures of an individual's socioeconomic status or position.

Within a particular society, patterns of health can be compared according to socioeconomic factors such as education, income, wealth, labour market participation, living conditions, and social class (Marmot et al., 2010). Collectively, these factors are commonly characterised as "the conditions in which people are born, live, work, and age" (CSDH, 2008; WHO, 2024). They are shaped by cultural norms (Rice & Liamputtong, 2023), geography and demography (Diamond, 1998), and economic, social, health, and environmental policy (Allen et al., 2014).

Social determinants of Health (SDH) models provide a comprehensive framework for understanding why and how these factors influence health (BARHII, 2023; Barton & Grant, 2006; Dahlgren & Whitehead, 2021; Frieden, 2010; Huynen et al., 2005; Labonte & Torgerson, 2005; World Health Organization, 2010). These models help to explain why certain individuals may have a higher risk of disease, or poorer health outcomes following illness. They also help to explain why the consequences of disease may have a greater impact upon the lives of some and not others. Put simply, SDH models describe how the broader social, economic, and political policies of a nation, shape the conditions through which exposure to more proximal risks, such as material deprivation, may occur.

For example, the distribution of goods and economic resources within a population are, to some extent, 'downstream' of governmental policy. SDH models emphasise that the distribution of these resources is a fundamental contributor to the prevalence, risk, and impact, of various health outcomes. In practice, greater resources (such as income and wealth) enables access to key determinants of positive mental health, while also assisting individuals to minimise their exposure to stressors (Link & Phelan, 1995; Marmot et al., 2010).

This concept is elucidated in greater detail within the WHO Commission on Social Determinants of Health (CSDH) model. This framework describes how health outcomes are a product of multiple complex and dynamic interactions operating between the social, economic and political context defining a countries key institutions[20], and the proximal 'material' conditions defining an individual's day to day existence. In practice, this suggests that a countries socioeconomic and political mechanisms stratify populations according to characteristics such as income, wealth, education, occupation, social class, gender, and race or ethnicity. In turn, this stratification leads to individuals within a population experiencing differing levels of 'exposure' to a range of proximal risk or protective health factors. These include an individual's day to day material living circumstances, the daily psychosocial stressors they are exposed to, and the behavioural and biological factors, such as exercise, nutrition, and alcohol or tobacco consumption, that characterise their lives (World Health Organization, 2010).

Both physical *and* mental health outcomes have shown sensitivity to various measures of socioeconomic status and position. For example, the prevalence of common physical conditions, such as heart-disease, diabetes and obesity, increases with relative disadvantage (Banks et al., 2006; Pickett & Wilkinson, 2015). Likewise, the burden of mental ill health and illness is disproportionately carried by individuals with fewer financial resources, who tend to be of lower socioeconomic position or status (Allen et al., 2014, Kessler & Cleary, 1980). Reductions in mental wellbeing have demonstrated an association with various measures of material deprivation, including the experience of relative or absolute poverty (Lorant et al., 2007; Lund et al., 2010), low income (Enticott et al., 2016; Isaacs et al., 2018; Muntaner et al., 2004), low wealth (Ettman et al., 2020; Kendall et al., 2019), lower socioeconomic status (Lemstra et al., 2008), experiencing or worrying about debt (R. Jenkins et al., 2008; Reading & Reynolds, 2001; Turunen & Hiilamo, 2014), and financial hardship or household financial strain (Butterworth, Olesen, et al., 2012; Domènech-Abella et al., 2021; Foulds et al., 2014; French & Vigne, 2019; Kiely et al., 2015; Selenko & Batinic, 2011). Additionally, factors related to labour market participation like unemployment (Bambra & Eikemo, 2008; Latif, 2015; Montgomery, 1999; Stuckler et al., 2009, 2011), job insecurity (Ferrie, 2002; Marmot et al., 2001), precarious or irregular employment (Benach &

[20] Such as the labour market, the education system, the type of governance in a country, a countries predominant culture and values, and macroeconomic, social, and public policies.

Muntaner, 2007), and involuntary job loss (Catalano et al., 2011), have also demonstrated robust associations with reduced mental health. Finally, even more distal factors, such as poor neighbourhood conditions (Halpern, 1995), economic recessions (Schrecker & Bambra, 2015), and higher national-level economic inequality (Kawachi & Subramanian, 2014; Layte, 2012; Layte & Whelan, 2014; Patel et al., 2018; Pickett & Wilkinson, 2010) are all associated with poorer mental health outcomes amongst those exposed to such conditions.

Importantly, socioeconomic disadvantages tend to cluster within individuals. Those with lower levels of education are more likely to earn a lower income, experience periods of unemployment, face housing insecurity, and reside in less safe neighbourhoods. This clustering produces a 'cumulative' socioeconomic disadvantage that, in turn, may significantly degrade health outcomes (Neadley et al., 2021; Schiltz et al., 2022).

Evidence of the association between poorer mental health and socioeconomic disadvantage has been affirmed by an array of systematic reviews and meta-analyses conducted over the past three decades. At least 25 review papers have summarised the influence of a diverse range of socioeconomic factors on mental health, using various populations, across individual, neighbourhood, and macro levels of analysis. The majority have found consistent evidence linking socioeconomic factors to poorer physical and mental health.

This includes reviews linking poorer mental health to unemployment, socioeconomic status and socioeconomic position (Feinstein, 1993; Fryers et al., 2003; Lorant, 2003; Muntaner et al., 2004; Paul & Moser, 2009), absolute and relative poverty (Iemmi et al., 2016; Lund et al., 2010), income (Thomson et al., 2022), debt (Fitch et al., 2011; Turunen & Hiilamo, 2014), housing disadvantage (Singh et al., 2019) and subjective financial satisfaction (Ngamaba et al., 2020). Several reviews have focused specifically on the relationship between socioeconomic factors and the mental health of children (LeMoult et al., 2020; Lemstra et al., 2008; Letourneau et al., 2013; Reiss, 2013; Russell et al., 2016). Additional reviews have also appraised the association between mental health and income inequality (Patel et al., 2018; Ribeiro et al., 2017; Tibber et al., 2022), and the association between mental health and neighbourhood-level disadvantage (Barnett et al., 2018; R. Richardson et al., 2015; Silva et al., 2016). Finally, reviews have systematically assessed the evidence linking macro level factors, such as economic policy, welfare provision, and economic recessions to mental health (Frasquilho et al., 2015; McAllister et al., 2018; McCartney et al., 2019).

Whilst this is not an exhaustive, nor systematically derived, list of all systematic reviews and meta-analyses that have been published assessing the relationship between measures of socioeconomic conditions and mental health, it represents a substantial body of research. Given the numerosity of reviews appraising the association between mental health and various socioeconomic factors, it is perhaps unsurprising to see the emergence of 'reviews of systematic reviews'. Lund and colleagues (2018) reviewed 289 systematic reviews and developed a conceptual framework summarising the major social/economic determinants of mental health disorders. They subsequently linked each determinant to the United Nations Sustainable Development Goals (SDG's). Moreover, Huggard and colleagues (2023) conducted a rapid review of 37 systematic reviews, published between 2015 and 2022, that assessed the relationship between any social determinant and mental health. They found that the experiences of violence, conflict, maltreatment, racism/discrimination, poor living conditions, employment and financial factors were all strongly associated with reduced mental health and mental illness.

The Present Review

Regardless of how socioeconomic status or position is assessed, experiencing disadvantage is reliably associated with poorer mental health. However, despite the abundance of systematic reviews and meta-analyses assessing the relationship between mental health and varying dimensions of socioeconomic position, a comprehensive and systematic evaluation of the direct impact of financial hardship on mental health outcomes remains to be completed.

Financial hardship measures differ markedly from other indicators of socioeconomic status, insofar as they directly evaluate whether an individual or household has forgone essential goods, facilities, or services, or experienced standards of living understood as subminimal relative to the society they live within, due to a lack of financial resources (Butterworth et al., 2012; Kiely et al., 2015; Whelan, 1993). The experience of financial hardship has been elegantly surmised by Mack & Lansley (1985) as "an enforced lack of socially perceived necessities". The inability to afford food, clothing, medical care, utility bills, and housing costs, or the seeking of financial aid from welfare organisations, friends, or families, are commonly assessed domains within measures designed to detect the experience of hardship.

Assessing deprivation via the direct inquiry afforded by hardship measures proffers several key empirical advantages over more commonly utilised measures of socioeconomic standing. Principally, income and wealth derived assessments of deprivation can be confounded by the moderating effects of wealth assets, the use of credit or debt to manage ebbs and flows in liquidity, the availability of non-cash benefits (such as resource sharing from family and friends), variations in personal taste or lifestyle decisions, and locational differences in living costs (Butterworth, Olesen, et al., 2012; Butterworth & Crosier, 2005). Similarly, proxy measures of socioeconomic status or position, such as occupational class, level of education attained, neighbourhood-level disadvantage, or employment status *infer* deprivation. Conversely, financial hardship measures encompass a direct, subjective assessment of privation stemming from insufficient financial resources. In other words, financial hardship measures directly inquire about whether an individual has experienced specific deprivations due to a lack of financial resources. Consequently, hardship measures are less prone to over and under-estimating associations with health outcomes (Burns, 2015; Foulds et al., 2014; Lahelma et al., 2006). Several studies have demonstrated that comprehensive indices directly assessing the subjective presence or absence of financial hardship, provide a superior estimation of the association between socio-economic status and health outcomes, compared to objective measures of income, wealth, education, or employment (Butterworth et al., 2012; Carle et al., 2009; Foulds et al., 2014; Heflin, 2016; Lorant et al., 2007).

Reviews bearing similarity to the present research have been undertaken. Firstly, a review by Frankham and colleagues (2020) focused on psychological factors associated with financial hardship, and the mechanisms underpinning this relationship. Secondly, Talamonti and colleagues (2023) reviewed the indirect association between financial hardship and population level mental health within the context of national and international financial crises. Thirdly, three reviews specifically focusing on the impact of food insecurity on mental health (Arenas et al., 2019; Maynard et al., 2018; Shankar et al., 2017). Each of these reviews broadly supported the relationship between deprivation and poorer mental health. However, none of them summarised existing evidence pertaining to the overall relationship between the experience of financial hardship and mental health. Thus, a comprehensive synthesis of evidence assessing the direct longitudinal relationship between financial hardship and mental health outcomes remains absent in the current literature.

Aims

The aim of this systematic review is to address this gap in the literature and synthesise existing evidence to better understand the longitudinal relationship between financial hardship and common mental health conditions. Given this, we examine the international literature to capture a broad non-clinical representation of individuals, across sexes, varying age groups and socioeconomic backgrounds, who report experiencing financial hardship.

In accord with the PI(E)CO(T)[21] framework, this review seeks to answer the following:

Are individuals (P), who experience financial hardship (E) at greater risk of experiencing worse mental health outcomes (O) compared to individuals who do not experience financial hardship (C) within studies using longitudinal methods (T)?

We will answer this question by:

1. Identifying the constructs and terms that have been used to define and measure financial hardship.
2. Evaluating the overall longitudinal relationship between financial hardship and common mental health conditions.
3. Assessing how the relationship between financial hardship and common mental health conditions varies according to:
    i. The measure of financial hardship used, and the specific domains of deprivation assessed.
    ii. The measure of common mental health conditions used.
    iii. The confounding factors assessed within analytical models.
    iv. The geographical location of the study.
    v. The study sample size.
    vi. When the study was conducted.
    vii. The duration of the study, the number of survey waves assessed, and the interval between them.
    viii. The analytical techniques employed to test the relationship between financial hardship and common mental health conditions.
4. Identifying key participant characteristics that may modify the relationship between financial hardship and common mental health conditions, including:
    i. Age
    ii. Sex
5. Critically appraising the quality of existing evidence.

Methods

[21] P – Population; I(E) – Intervention (Exposure); C – Comparison; O – Outcome; (T) – Timeframe

This systematic review was designed and conducted in alignment with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis Protocols (PRISMA-P) (Page et al., 2021). The protocol was registered with PROSPERO (CRD42024501037).

Search Strategy

A systematic literature search was conducted across five databases – Scopus, PsycINFO, MEDLINE, EMBASE and PubMED – between May to July of 2023, for studies that assessed the longitudinal relationship between financial hardship and common mental health conditions. Searches were restricted to peer-reviewed published articles in English.

Searches were not limited by the age, or date, of publication. This served dual aims. Firstly, it allowed us to evaluate the entire body of published evidence since inception. Secondly, this also allowed us to assess whether heterogeneity in the relationship between financial hardship and common mental health conditions can be explained by temporal trends or date of publication. The database search strategy was developed in consultation with a University of Sydney librarian. Search strings were composed of three key classes of terms, relating to financial hardship, mental health, and longitudinal study designs. Search terms were tested and refined to optimise sensitivity and specificity across each literature database. Key papers known to assess the longitudinal relationship between financial hardship and common mental health conditions were shortlisted, and search terms were validated against the presence of these key papers in search outputs. The finalised search strings, applied to extract relevant articles from each database, are detailed in Appendix A.1.

Inclusion and Exclusion Criteria

Studies were included if they were an original, peer-reviewed research paper, published in English, using prospective longitudinal data, and longitudinal analysis techniques, to examine the longitudinal relationship between experiencing financial hardship and mental health. Studies that used convenience sampling, that did not examine risk factor/outcome relationships longitudinally, or included solely objective measures of financial hardship (such as income or wealth based measures of deprivation) were excluded. The complete inclusion and exclusion criteria are available in Appendix A.2.

With respect to sampling, studies were excluded if they made use of convenience sampling methods. This was defined as samples compiled using snowballing techniques, purposive sampling, quota sampling, accidental sampling, volunteer sampling, or any sample derived from an online advertisement via social media or a crowdsourcing data collection platform such as MTurk. The aim of this restriction was to minimise the inclusion of studies comprising samples at high risk of selection bias. Similarly, studies assessing clinical samples, selected on the basis of a pre-existing mental health condition were also excluded. This exclusion was designed to reduce the impact of factors that may confound the association between financial hardship and mental health[22].

Regarding methodology, in order to solely review research that assessed the focal relationship *longitudinally*, studies that used a single wave of data, comprised a retrospective longitudinal design, or analysed repeated cross-sections, were excluded. Moreover, studies were limited to those containing (1) a measure of mental health or common mental health conditions as an outcome; (2) a measure of financial hardship as a predictor; and (3) a test of the association, in this direction, between the two. Studies that did not conform to these requirements were excluded.

In scope financial hardship measures were defined according to precise criteria. Specifically, included studies were required to contain a measure of financial hardship that assessed deprivation at an individual level. Additionally, the measure of financial hardship was required to specifically ask whether an individual has experienced financial difficulty, or forgone specific goods or services due to a lack of money. In practice, this meant studies only containing assessments of familial or neighbourhood level deprivation were excluded. This also meant studies that only measured financial adversity using income alone (such as studies defining relative poverty according to some ratio of national median income), or studies that only inferred hardship due to some objectively defined indicator (such as the lack of a vehicle, or according to housing tenure) were excluded. Finally, studies were excluded if they only assessed an indirect association between hardship and mental health across generations, or between different individuals[23]. The aim of this restriction was to only review

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[22] For example, it is possible that specific mental health diagnoses may hold stronger associations with financial hardship than others. Similarly, compared to healthy controls, the experience of a mental health condition may be more strongly associated with financial hardship. In both instances, bias may be introduced to the overall association. Taking this a step further, particularly severe clinical diagnoses can have multifactorial causes (Uher & Zwicker, 2017), making it difficult to disentangle the specific effects of individual stressors, such as financial hardship, on mental health. Finally, serious mental health conditions often precede financial difficulties due to associated declines in work productivity, spells of unemployment, or financial mismanagement. Taken together, excluding clinical populations will mitigate the confounding effects of reverse causal pathways, and pre-existing mental health conditions, in order to elucidate the independent effect of financial hardship on mental health.

[23] For example, where hardship is reported by parents, and mental health outcomes are reported by their children.

studies assessing the focal association within the same individuals, in order to capture the unique effect of financial hardship on mental health.

Screening Procedure

Studies underwent two-stage dual screening prior to inclusion. Screening was facilitated via use of a novel semi-automated software platform (AutoLit, Nested Knowledge). Firstly, all records identified by database searching were title and abstract screened by one author (JT). 25 percent of all records were randomly allocated and second screened (CC, SO, and TS). Discrepancies were adjudicated by consensus (including PB). Using information gained from the preceding screening decisions made by human reviewers, the remaining 75 percent of records were secondary title and abstract screened using an automated AI screener built into the Nested Knowledge AutoLit review software. Discrepancies between the AI screener and the author (JT) were reassessed and adjudicated by JT.

Full-text screening was undertaken by two independent reviewers. JT completed full-text screening of all articles, while secondary full-text screening of all articles was completed by CC, SO, and TS – each of whom were randomly allocated one-third to review. Discrepancies on article inclusion were resolved by a third reviewer.

Data Extraction

Data extraction was completed on all included studies by the author (JT). Instances where data extraction was ambiguous were resolved by consensus with all authors (JT, PB, CC, SO, TS). Authors were contacted via email for study clarification or where additional information was required.

Information extracted from each study included: the study origin country(s), region(s), and/or city(s); the study setting; whether the survey used was nationally representative; the survey unit of analysis; how the survey was undertaken (modality); the analytic sample size; n of males and females; n of observations; sample age range and mean; financial hardship measure used (including domains assessed, and the number of items contained within the measure); the measure of mental health used; the statistical technique(s) used; confounders assessed; and the statistical significance of all bivariate and multivariate tests assessing the relationship between financial hardship experience and mental health.

Risk of Bias/Quality Assessment

Study quality was assessed using items 1 and 2 from the Joanna Briggs Institute Checklist for Cross-Sectional Studies, and 10 items from the Joanna Briggs Institute Checklist for Cohort Studies (Aromataris et al., 2024)[24].

All included studies were independently assessed by two reviewers. The author (JT) quality assessed all studies. Secondary quality assessment was shared by all supervisory team members (CC, PB, SO, and TS), who were randomly allocated approximately one-quarter of included studies to review. The total number of items rated as 'yes' by both reviewers for each paper were summed and then divided by the maximum number of possible 'yes' ratings (i.e., 24) to produce a percentage score out of 100.

Results

Screening

Abstract Screening

A total of 8,672 records were identified via database searching. Following de-duplication 3,238 studies were abstract screened. 196 records were advanced for full text review. Inter-rater reliability for title and abstract screening was high (94.4%).

The most common reasons for exclusion at the abstract stage were studies not detailing evidence of an individual level financial hardship measure (1,348 studies), not testing an association between financial hardship and mental health in any analysis (525 studies), not containing a mental health measure (466 studies), and mental health not being specified as an outcome measure in any analysis (309 studies) (see Figure 1 below for PRISMA flow diagram).

Full Text Screening

[24] Specifically, item 1 from the Joanna Briggs Institute Checklist for Cross-Sectional Studies asks, "*Were the criteria for inclusion in the sample clearly defined?*" and item 2 asks, "*Were the study subjects and the setting described in detail?*". Item 3 of the Checklist for Cohort Studies, which asks "*Was the exposure measured in a valid and reliable way? (i.e. Risk/protective factors)*", was excluded from the quality assessment. This decision was made due to the substantial variation between measures of financial hardship, which precluded meaningful quality assessment. Additionally, as previously noted, there is no universally agreed upon definition of what constitutes a valid and reliable measure of financial hardship, and thus there is no 'yardstick' to assess measures against. Given this, one of the aims of the review is to assess whether the association between financial hardship experience and mental health varies as a function of various dimensions of the hardship measures used.

A total of 196 records were full text screened. Ninety-four were included in the review. As per title and abstract screening, inter-rater reliability remained high for full text screening (87.2%).

The most common reasons for exclusion at the full text stage included, the paper not containing an individual level measure of financial hardship (34 studies), not containing a measure of mental health (15 studies), not utilising longitudinal analysis techniques (14 studies), or having drawn a sample via convenience or sub-sampling techniques (12 studies).

A complete reference list detailing all 94 included studies is provided in Appendix A.3.

PRISMA Flow Diagram

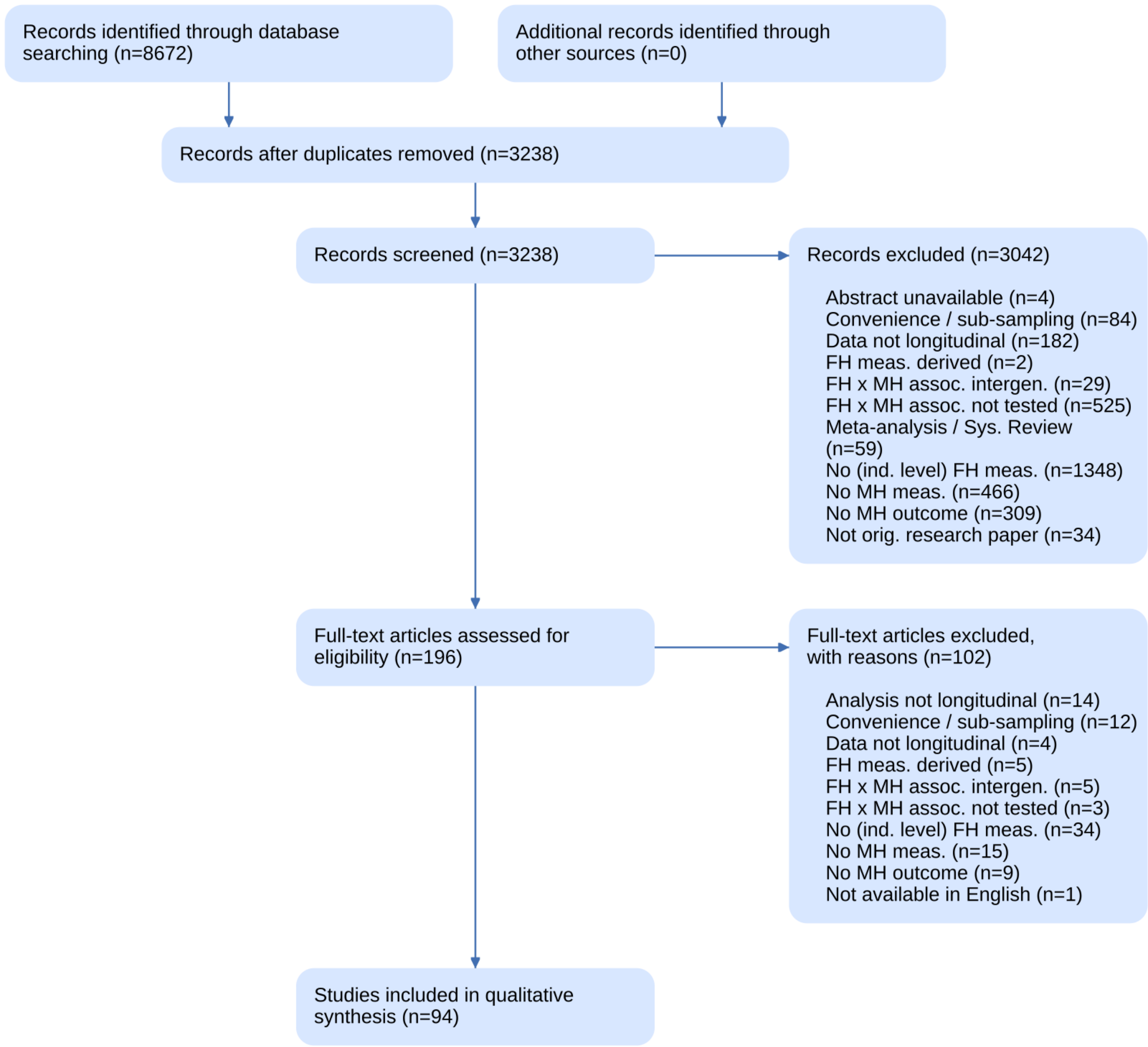

Figure 1
PRISMA Flow Diagram.
FH = Financial Hardship; MH = Mental Health

Quality Assessment - Joanna Briggs Institute Checklist for Cohort Studies

Overall, the quality of included studies was high, with an average quality rating of 80 percent. Additionally, 96.8 percent of included studies were rated with a score of at least 70 percent. Lower quality ratings were generally due to studies not reporting details of follow-up rates, reasons for loss to follow-up, or studies not utilising strategies to address incomplete follow up. Overall agreement between independent reviewers was high (91.8 percent). Full details of the criteria each paper was assessed against are presented in Appendix A.18.

Characteristics of Included Studies

Sample Characteristics

Key aggregated sample characteristics of all included studies are summarised in Table 1 – detailed characteristics are presented in Appendix A.4. The 94 included studies represented a total sample of 497,001 persons. 15 studies utilised female only samples, however, the majority (54.7%) comprised roughly equal males to females (see Table 1 below).

Table 1
Aggregated sample characteristics of included studies

Sample Characteristics (Persons)	n	%	Papers
Total Sample			
Min	104		94
Max	41,909		94
Average	5,287		94
Male	175,488	41.3%	86
Female	249,546	58.7%	86
Total	**497,001**	**100.0%**	**94**
Age Range Category			
10-18 - Adolescence	4	5.0%	80
10-39 - Adolescence to Young Adults	7	8.8%	80
10-65 - Adolescence to 65	10	12.5%	80
10-65+ - Adolescence to Old Age	24	30.0%	80
19-39 - Young Adults	5	6.3%	80
19-65 - Young Adults to 65	4	5.0%	80
19-65+ - Young Adults to Old Age	9	11.3%	80
40-65 - Midlife	2	2.5%	80
40-65+ - Midlife to Old Age	15	18.8%	80

Study Characteristics

Included studies spanned 26 countries. The three most commonly surveyed countries were the USA (n = 29)[25], Australia (n = 16) and the UK (n = 11), representing almost 60 percent of all included studies (Table 2). Moreover, almost 80 percent of countries included in this review were represented by only one 1 or 2 studies. As detailed in Table 2, four studies utilised data from more than one country (Barthel et al., 2017; McCarthy et al., 2018; Porter et al., 2021, 2022).

A total of 63 unique surveys/datasets were used across the set of included studies (see Appendix A.5). Fifty-three studies in this review utilised surveys conducted at the national level, of which 38 were nationally representative (Table 2). The most commonly utilised surveys/datasets were the Household, Income and Labour Dynamics in Australia (HILDA) survey (n = 4) and the Korea Welfare Panel Study (KOWEPS) of South Korea (n = 4) (Appendix A.5).

Studies included within this review were published between 1987 and 2023. Across the 36-year study period reviewed, there was an increase in the number of studies assessing the relationship between financial hardship experience and mental health. The majority of included studies were published since 2018, particularly in 2021 (12 studies) and 2022 (13 studies).

Detailed descriptive analysis summarising further characteristics of included studies, such as publication year and survey setting, can be found in Appendix A.6.

[25] The United States of America was also assessed in a study by Barthel and colleagues (2017) alongside Canada (Table 2).

Table 2
Countries represented within included studies and number of studies utilising nationally representative surveys

Study Characteristic	n
Country(s) Assessed	
United States of America	29
Australia	16
United Kingdom	11
Canada	5
China	4
South Korea	4
Sweden	4
Taiwan	3
Ethiopia; India; Peru; Vietnam	2
Germany	2
Ghana	2
South Africa	2
Switzerland	2
Belgium	1
Canada; United States of America	1
Côte d'Ivoire; Ghana	1
Czech Republic	1
France	1
Ireland	1
Netherlands	1
New Zealand	1
Scotland	1
Singapore	1
Zambia	1
Nationally Representative	
Yes	38
No	15

Study Duration

Studies were most commonly conducted over a period spanning 0-1 years (n = 16). The majority of studies (56%) spanned a duration of 0-4 years. The average study span was 5.4 years. One study was conducted over a period of 23-24 years.

Survey Waves

The majority of included studies within this review (62%) analysed two or three waves of data. Thirty-two studies analysed two waves of data, and 26 studies analysed three waves of data. A further 15 studies also analysed four waves of data. The maximum number of waves analysed was 20 waves of data.

Survey Wave Measurement Interval

The measurement interval between survey waves across the 94 included studies varied widely. The shortest survey wave interval was one week (0.25 months). The longest survey interval between waves was nine years (108 months). Studies most commonly utilised surveys that had a measurement interval of one year (n = 27). Eighteen surveys had a measurement interval of at least two years, and 10 surveys had a measurement interval of at least three years.

COVID-19

The COVID-19 pandemic was a focus of 14 of the total included studies. Six of these were published in each of 2021 and 2022, and two were published in 2023.

Characteristics of Financial Hardship Measures

Across the 94 studies included in this review, financial hardship measures were categorised according to two key criteria: (1) whether the measure assessed the experience of *specific* privations (e.g. 'in the past 12 months have you gone without food, medication, or clothing due to a lack of money?'), or an individual's global *perception* of their current financial situation (i.e. how they 'feel' about their current financial situation); and (2) 'how' the measure was implemented – i.e., was the measure implemented using *individual items* to assess discrete domains of privation, a *multi-item scale*, or a *general question* that inquired about an individual's financial position (e.g. 'how well would you say you are managing financially these days – (1) living comfortably; (2) just about getting by; and (3) finding it difficult or very difficult?').

With respect to the first criteria, 62 studies assessed the experience of *specific* privations, and 30 studies assessed an individual's global *perception* of their current financial situation. Two studies did not provide enough information to make a determination and were assigned a status of 'Not stated'. With respect to the second criteria (i.e., 'how' the hardship measure was implemented), 17 studies used individual items to assess the experience of financial hardship, 49 studies used a multi-item scale measure, and 25 studies used a 'general' question(s) to ascertain the overall quality of an individuals' financial situation. A further three studies did not provide enough information to identify how they operationalised financial hardship, and they were assigned as 'Not stated'. Full details of the disaggregation of financial hardship measures according to these two criteria is provided in Appendix A.9.

Financial hardship measures were also characterised with respect to the number of items they contained and the number of hardship domains they assessed. This analysis was stratified according to whether financial hardship was assessed using multi-item or individual item measures. Details of this descriptive analysis can be found in Appendix A.10.

A detailed summary of the financial hardship measures used within each study are provided in Appendix A.8.

Domains of Financial Hardship Assessed

The 62 studies that assessed the direct experience of hardship used 110 different measures of deprivation (via either multi-item scales or individual items)[26]. Given the similarities across these items, they were collapsed into 19 distinct groupings, each pertaining to a different domain of deprivation. Within the subset of 30 studies that used a measure assessing an individual's *global perception* of their current financial situation, items fell into two of the 19 distinct domain categories – *General Financial Hardship/Financial situation* (assessed within 18 studies) or *Perceived Hardship* (assessed within nine studies).

These distinct domains (and details of the number of studies that include each measure) are shown in Table 3: Food related deprivation was the most frequently assessed hardship domain, with 42 studies assessing this construct. This was followed by difficulty paying utility bills (assessed within 24 studies), difficulty heating or cooling one's home (assessed

[26] Note, four studies that used a multi-item scale assessed *perceived* hardship, as opposed to assessing specific privations. Hence why the hardship measures used in only 62 studies are discussed above with respect to the domains of hardship a measure contained, as opposed to the total of 66 studies that used individual item and multi-item measures of hardship (i.e., 17 individual item hardship measures + 49 multi-item hardship measures = 66).

within 17 studies), difficulties meeting mortgage/rent payments (assessed within 16 studies), and inability to pay medication, doctors, and other health related costs (assessed within 15 studies). 12 studies assessed whether respondents had pawned or sold personal items to make ends meet, 11 studies assessed the experience of cashflow problems, and 11 studies assessed whether respondents had received financial assistance from community organisations or government income support payments.

Of note, there were instances where multi-item scales contained items assessing whether an individual was currently unemployed or had recently experienced unemployment. Whilst unemployment does not necessary align with the definition of financial hardship this review is concerned with, the majority of items in these scales did and were therefore included in our analysis. However, the specific domain categories listed in Table 3 are limited to those consistent with assessments of material privation.

Measures of Mental Health Utilised

Of the 94 studies included in this review, 55 included a measure of depression, 20 included a measure of anxiety, four included a measure of stress, and 42 included a measure of general mental health/distress. Measures of stress were assessed based on perceptions (Perceived Stress Scale), and experience of specific 'stress' symptoms as asked in the DASS. Additionally, 16 studies utilised a diagnostic measure of mental health, while 78 did not. A detailed distribution of mental health measures used across all included studies is shown below in Figure 2. Note, use of the ICD-10 criteria for depression and anxiety relate to survey questions based on the ICD-10 diagnostic criteria (Amegbor et al., 2021), and clinical diagnoses retrieved from registry data (Bialowolski et al., 2021).

Table 3
No. of studies that assessed each hardship domain

Hardship Domain	Description	Specific Deprivations	Perceived Deprivations	Total
Cashflow	Difficulties with income/cashflow.	11	0	**11**
Clothing	Experiencing an inability to purchase new clothing, or continuing to wear clothing/shoes in a state of disrepair.	7	0	**7**
Debt	Difficulties with debt.	5	0	**5**
Difficulty Supporting Family/Children	Experiencing an inability to pay for essential items for one's family/children.	3	0	**3**
Emergency Funds	Not being able to raise money in the event of an emergency.	3	0	**3**
Financial Support	Having received financial assistance from community organisations government income support payments.	11	0	**11**
Food	Food deprivation (in terms of quantity, quality, and or variety) due to a lack of money.	42	0	**42**
General FH/Financial Sit.	Perceiving one's general financial situation to be difficult.	3	18	**21**
Heating/Cooling	Experiencing an inability to adequately heat one's home in winter, or cool one's home in summer.	17	0	**17**
Help from Friends/Family	Having received financial assistance from friends or family.	6	0	**6**
Household Repair/Maintenance	Experiencing a lack of money to complete necessary repair, replacement, or maintenance of essential household items.	3	0	**3**
Medication/Doctors/Health	Experiencing an inability to pay for, or foregoing, medication, doctors' appointments, and/or necessary health related activities.	15	0	**15**
Mortgage/Rent	Experiencing difficulties meeting payments related to housing costs.	16	0	**16**
Not Stated		2	3	**5**
Pawned/Sold	Pawning or selling of personal items to make ends meet.	12	0	**12**
Perceived Hardship		1	9	**10**
Social/Leisure	Not having enough money to participate in social/leisure activities.	4	0	**4**
Transport	Not having enough money to pay transport costs.	2	0	**2**
Utilities	Experiencing an inability to pay for utilities, such as electricity, gas, oil, telephone, or water bills.	24	0	**24**

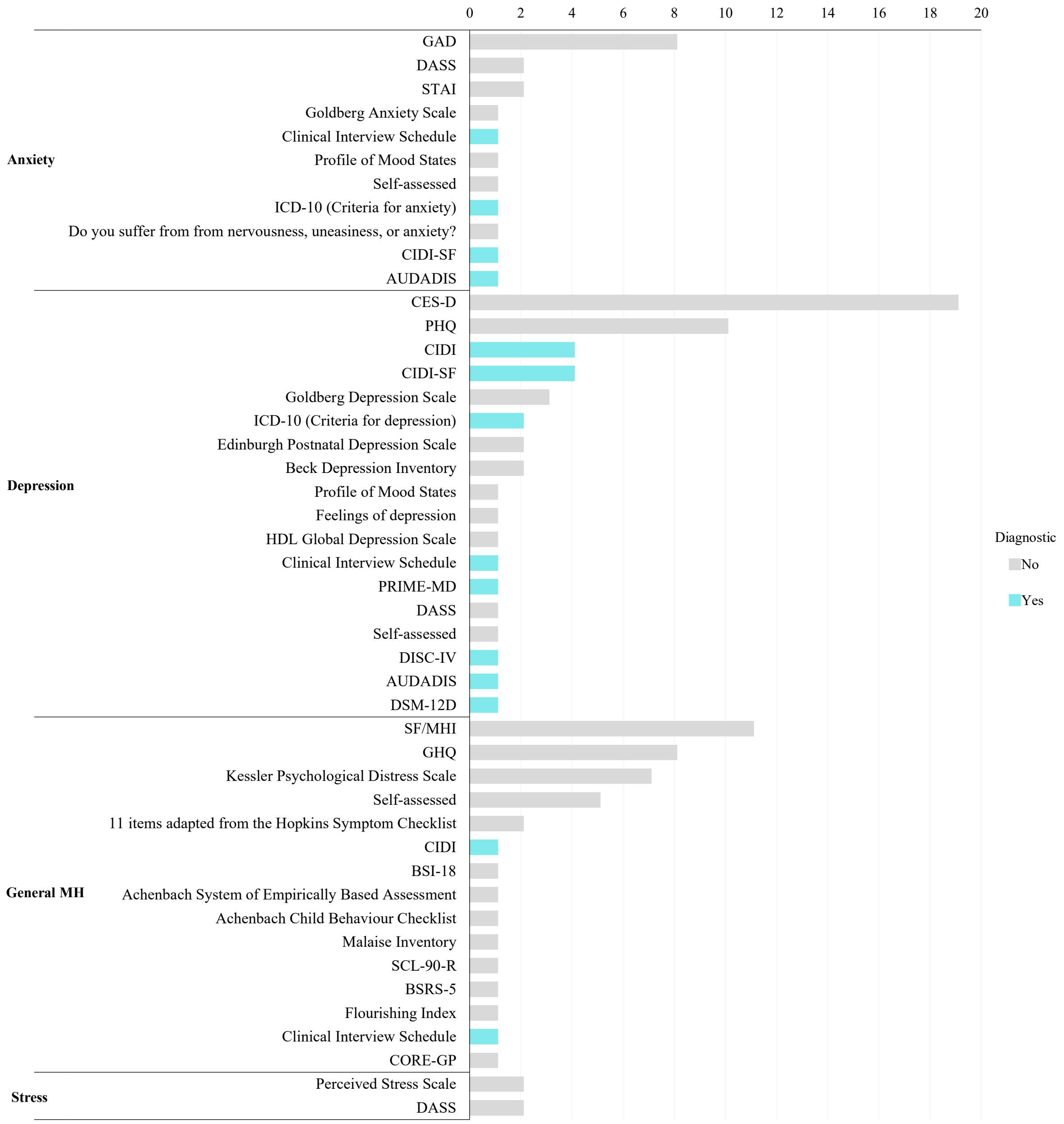

Figure 2
Measures used to assess mental health

Statistical/Analytical Approach

In total, 55 different analytical approaches were employed across the 94 included studies. A comprehensive list of all strategies is detailed in Appendix A.11. Given the diversity of approaches employed, analytic techniques belonging to distinct statistical families were collapsed into four groups. Approaches involving various regression models were the most common (n = 72). The use of growth curve (and trajectory) modelling approaches (n = 10), increased in frequency as publications became more recent, whereas, SEM approaches (n = 12) tended to be more common in earlier publications. One paper made use of correlational analysis as its primary statistical approach.

While the vast majority of studies made use of regression approaches, there was variation in how this was applied to examine the relationship between financial hardship experience and mental health. For example, several studies made use of random-effects or generalised estimating equation approaches to examine the focal relationship using longitudinal data, but didn't differentiate between-person changes from within-person changes (Austin et al., 2018; Manuel et al., 2012; Whitsett et al., 2019). Studies limited to two waves of data, commonly used regression modelling to contrast how hardship experience at wave 1 or wave 2 predicted mental health at wave 2 (Dickerson et al., 2022; Mendes de Leon et al., 1994). Similarly, some studies employed regression models that stratified participants according to their mental health status at wave 1, in order to examine the effect of hardship on the onset or continuity of poorer mental health over time (Butterworth et al., 2009; Roberts et al., 1997; Skapinakis et al., 2006). Additionally, papers that made use of a larger number of study waves, commonly employed fixed effects, mixed effects, or Mundlak models, to focus directly on the within-person association of hardship experience and mental health, and assess how changes in the experience of hardship was associated with changes in mental health over time (Bentley et al., 2023; Heflin et al., 2005; Kiely et al., 2015; McCarthy et al., 2018). In some cases multilevel models were employed to consider an individual's social setting in the relationship between hardship and mental health (Cole & Tembo, 2011). With respect to other approaches, it was common for SEM and cross-lagged dynamic panel models to examine the concurrent effects of hardship on subsequent mental health, and of mental health on subsequent hardship. Latent class modelling approaches were used to identify profiles of mental health over time and the extent to which financial hardship was associated with these (Batterham et al., 2018; Moulton et al., 2023). A table summarising analytic approaches is presented in Appendix A.12.

Confounders Assessed

A total of 373 unique constructs were used as covariates within the included studies. A comprehensive list, along with frequencies, is detailed in Appendix A.13. Similarities between items enabled them to be collapsed into twenty distinct groups, as detailed below in Table 4. Most studies included in this review (n = 75) controlled for aspects of participant demography (such as age, sex, sexuality, ethnicity, country/state/region of residence). Similarly, 57 studies also controlled for relationship status/relationship factors (such as marital/relationship status, marital stress, partners mental health, relationship satisfaction/quality, and whether cohabiting/living with partner or alone) and 54 controlled for educational factors (such as years of education, or highest level achieved). A total of 27 studies controlled for prior mental health (such as a prior diagnoses, self-rated mental health, or baseline levels of psychological distress). A total of 79 studies contained at least one measure of a respondent's socioeconomic status (i.e., 'SES – Any' in Table 4) in addition to measuring hardship (such as income, wealth, employment status, level of education, housing tenure, and area-level disadvantage).

Additionally, 24 studies controlled for at least one aspect of participant demography *and* pre-existing mental health; while 21 studies controlled for at least one aspect of participant demography, pre-existing mental health, *and* socioeconomic status (Table 4).

Table 4

Number of studies that contained a control in each grouping

Control Group	n
Demographics	75
Relationship	57
Physical Health	41
Other	33
Family factors	31
Mental Health	27
Adversities	16
Neighbourhood factors	15
Study Methodology/Factors	14
Alcohol/Smoking/Drug use	10
Mastery/Locus of Control	8
COVID-19	7
Personality	5
SES - Education	54
SES - Employment & Labour Market Characteristics	48
SES - Income/Wealth	41
SES - Housing	14
SES - General	10
SES - Hardship	5
SES - Childhood	2
* SES - Any	79
Demographics + Mental Health	24
Demographics + Mental Health + SES	21

* *SES – Any* refers to the number of studies that contained at least one measure of any SES factor

Relationship between Financial Hardship and Mental Health

Bivariate and Multivariate Outcomes

The studies included within this review varied extensively, particularly with respect to the analytic approaches they employed, and their operationalisation of financial hardship and mental health. Given this, our analysis focuses on whether the studies demonstrated a significant association between hardship and mental health, irrespective of the study approach.

Across the 94 studies included in this review, 23 bivariate assessments and 116 multivariate assessments evaluated the association between financial hardship and mental health. All 23 bivariate analyses demonstrated that the experience of financial hardship was significantly associated with poorer mental health. Of the 116 multivariate analyses, 101 (87.1%) demonstrated a significant association between financial hardship experience and poorer mental health (Table 6).

Given all of the assessed bivariate analyses found a significant association between financial hardship experience and poorer mental health, the next section focuses solely on exploring sources of heterogeneity in the studies that used multivariate analyses.

Key characteristics of studies that did not demonstrate a multivariate association between financial hardship and reduced mental health

Sample Characteristics

Of the 15 multivariate assessments that did not demonstrate an association between financial hardship experience and reduced mental health, 14 (93.3%) came from studies that used samples of less than 3,000 participants. Of these studies, four apiece came from studies utilising samples ranging in age from 10-65 and 10-65+, and three came from studies using samples spanning the midlife to old age period (40-65+). One each came from studies using samples ranging in age from 10-39, 19-39, 19-65, and 19-65+ (Table 5). Of note, while all 94 studies included in the review provided data on sample size, only 80 studies provided information on age range. Multivariate outcomes according to the proportion of males in study samples were also analysed – details of this are presented in Appendix A.14.

Table 5
Multivariate outcomes by study sample size and age range of sample

Sample Characteristics	No		Yes	
	n	%	n	%
Sample Size				
100 - 249	1	25.0%	3	75.0%
250 - 499	3	16.7%	15	83.3%
500 - 999	3	18.8%	13	81.3%
1,000 - 1,999	4	19.0%	17	81.0%
2,000 - 2,999	3	17.6%	14	82.4%
3,000 - 4,999			12	100.0%
5,000 - 9,999	1	11.1%	8	88.9%
10,000 - 19,999			12	100.0%
20,000 - 45,000			7	100.0%
Age Range Category				
10-18 - Adolescence			4	100.0%
10-39 - Adolescence to Young Adults	1	14.3%	6	85.7%
10-65 - Adolescence to 65	4	28.6%	10	71.4%
10-65+- Adolescence to Old Age	4	12.1%	29	87.9%
19-39 - Young Adults	1	20.0%	4	80.0%
19-65 - Young Adults to 65	1	20.0%	4	80.0%
19-65+ - Young Adults to Old Age	1	7.7%	12	92.3%
40-65 - Midlife			4	100.0%
40-65+ - Midlife to Old Age	3	18.8%	13	81.3%

* Note, sample size data provided in all 94 studies; Age range data only provided in 80 studies

Study Characteristics

With respect to country, of the 15 multivariate assessments that did not demonstrate an association between financial hardship experience and reduced mental health, eight were analysed on samples from the United Kingdom, two on samples from Australia, and one apiece on samples from China, France, The Netherlands, South Africa, and the United States of America (Table 6).

Moreover, of the 15 assessments that did not demonstrate a multivariate association between hardship experience and poorer mental health, two came from studies using the 2000 Psychiatric Morbidity Survey (UK), two from the Whitehall II Survey (UK), two from the Personality and Total Health (PATH) Through Life study (AU), one from the Southampton Women's Survey (UK), one from the Netherlands Study of Depression and Anxiety (The Netherlands), one from the Trends and Implications of Poverty and Social Disadvantages in Hong Kong survey (China), one from the Well-being Survey (USA), and one from the Trajectoires Epide´Miologiques en POpulation (TEMPO) COVID-19 survey (France). Four assessments that did not show a positive association were based on samples from unnamed surveys/datasets. Full details of multivariate outcomes with respect to the survey/dataset used are presented in Appendix A.15.

Further analysis of multivariate outcomes with respect to characteristics of included studies, such as study setting, study duration, survey waves utilised, and survey wave measurement interval is presented in Appendix A.16.

Table 6

Multivariate outcomes by assessment, country of study, and whether the sample used was nationally representative

Study Characteristic	No		Yes	
	n	%	n	%
Assessment				
Bivariate			23	100.0%
Multivariate	15	12.9%	101	87.1%
Country				
Australia	2	9.5%	19	90.5%
Belgium				
Canada			6	100.0%
Canada; United States of America			2	100.0%
China	1	20.0%	4	80.0%
Côte d'Ivoire; Ghana			1	100.0%
Czech Republic			1	100.0%
Ethiopia; India; Peru; Vietnam			2	100.0%
France	1	100.0%		
Germany			2	100.0%
Ghana			1	100.0%
Ireland			1	100.0%
Netherlands	1	100.0%		
New Zealand			2	100.0%
Scotland			1	100.0%
Singapore			1	100.0%
South Africa	1	50.0%	1	50.0%
South Korea			4	100.0%
Sweden			5	100.0%
Switzerland			4	100.0%
Taiwan			3	100.0%
United Kingdom	8	44.4%	10	55.6%
United States of America	1	3.2%	30	96.8%
Zambia			1	100.0%
Nationally Representative				
Yes	2	4.5%	42	95.5%
No	13	18.1%	59	81.9%

Financial Hardship Measures

Specific vs Perceived Deprivation

Of the 116 multivariate estimates assessed in this review, 37 evaluated the relationship between financial hardship and mental health using a measure of an individual's global *perception* of their current financial situation (i.e., Perceived deprivation/general finances), and 77 used a measure of hardship that assessed the experience of specific deprivations[27]. Overall, 34 out of 37 (91.9%) assessments using 'perceived' measures of hardship demonstrated a multivariate association between financial hardship experience and poorer mental health. For assessments that used a 'specific' measure of hardship, 65 out of 77 (84.4%) demonstrated a multivariate association between financial hardship experience and subsequent poorer mental health (Table 7).

Measure Implementation

With respect to 'how' financial hardship measures were implemented, of the 116 multivariate estimates assessed, 32 estimates evaluated the relationship between financial hardship and mental health using a general financial question, 62 used a multi-item scale, and 19 used individual items[28]. Of the 32 assessments that operationalised financial hardship using a general financial question, 29 (90.6%) demonstrated an association between financial hardship experience and poorer mental health. Similarly, of the 62 assessments made using a multi-item scale, 50 (80.6%) found a multivariate relationship between financial hardship experience and poorer mental health. Finally, all 19 (100%) of the assessments that utilised an individual item to measure financial hardship demonstrated a significant association between hardship experience and poorer mental health (Table 7).

Additional analyses were conducted to assess multivariate outcomes with respect to the number of total items, and the total number of distinct domains of hardship, assessed within multi-item and individual item measures of financial hardship. Details of this analysis are presented within Appendix A.17.

Specific Constructs Assessed

[27] It was unclear what 'type' of financial hardship measure was used for two assessments. These were categorised as 'Not stated'.
[28] It was unclear how the measure of financial hardship was implemented within three estimates, and these are categorised as 'Not stated'. All three of these estimates demonstrated a significant association with mental health.

Finally, the 116 multivariate estimates assessed in this review were disaggregated according to the specific hardship construct assessed. The number of times each specific hardship construct was evaluated, and the proportion demonstrating significant and non-significant associations with mental health, are detailed in Table 7.

The majority of assessed hardship constructs consistently demonstrated a multivariate association with mental health. It is worth noting that hardship constructs demonstrating the lowest proportion of multivariate associations with mental health, such as clothing, emergency funds, household repair/maintenance, and social/leisure, were evaluated in fewer than 10 assessments. Thus, this lower proportion of significant associations may simply be an artefact of their smaller sample size.

Mental Health

Of the 116 multivariate estimates assessed in this review, 51 evaluated the relationship between financial hardship experience and a measure of depression, 43 with a measure of general mental health, 18 with a measure of anxiety, and four with a measure of stress.

Of the 51 estimates that assessed the relationship between financial hardship experience and a measure of depression, 47 (92.2%) demonstrated a significant multivariate relationship. Similarly, 37 out of 43 (86%) estimates assessing general mental health, 15 out of 18 (83.3%) estimates assessing anxiety, and two out of four (50%) estimates assessing stress found a significant association between financial hardship experience and poorer mental health (Table 7).

Confounders Assessed

A total of 75 studies controlled for at least one aspect of participant demography. Within these studies, 96 multivariate assessments of the relationship between financial hardship and mental health were conducted. Of these 96 assessments that adjusted for participant demography, 82 (85.4%), demonstrated a significant association between financial hardship experience and mental health. Similarly, a total of 27 studies controlled for pre-existing mental health. These studies contained 35 multivariate assessments, of which 28 (80.0%) remained statistically significant after control. Finally, 79 studies controlled for at least one aspect of socioeconomic status. These 79 studies contained 98 multivariate assessments of the relationship between financial hardship and mental health, of which 83 (84.7%) remained statistically significant following adjustment (Table 7).

Further, an analysis of outcomes with respect to combinations of controls was also undertaken. A total of 24 studies controlled for demography *and* pre-existing mental health. These studies contained 32 multivariate assessments of the focal relationship, of which 26 (81.3%) remained statistically significant after adjustment. Similarly, 21 studies controlled for demography, pre-existing mental health *and* socioeconomic status. These studies contained 28 assessments of the relationship between financial hardship and mental health, of which 22 (78.6%) remained statistically significant after adjustment (Table 7).

Taken together, these results demonstrate that the association between financial hardship experience and poorer mental health was robust to a wide array of controls included in multivariate models that (1) have previously been associated with reduced mental health, and (2) reflect items commonly included within social determinants of health (SDH) models assessing related constructs of socioeconomic status and position (such as level of education, and income). Notably, the most compelling finding from this analysis is that the relationship between financial hardship experience and poorer mental health remained statistically significant in the majority of assessments that controlled for participant demography, pre-existing mental health *and* associated socioeconomic factors. This result highlights the strength of the relationship between financial hardship experience and poorer mental health.

Table 7
Multivariate outcomes by characteristics of financial hardship measures, mental health measures, and included controls

Outcome	No		Yes		Total	
	n	%	n	%	n	%
1. Financial Hardship						
FH Measure - Type						
Not stated			2	100.0%	**2**	**100.0%**
Perceived deprivation/general finances	3	8.1%	34	91.9%	**37**	**100.0%**
Specific deprivations experienced	12	15.6%	65	84.4%	**77**	**100.0%**
FH Measure - Implementation						
Not stated			3	100.0%	**3**	**100.0%**
(Multi-item) Scale	12	19.4%	50	80.6%	**62**	**100.0%**
General financial question(s)	3	9.4%	29	90.6%	**32**	**100.0%**
(Individual) Item(s)			19	100.0%	**19**	**100.0%**
FH - Construct Groups						
Cashflow	2	11.8%	15	88.2%	**17**	**100.0%**
Clothing	3	33.3%	6	66.7%	**9**	**100.0%**
Debt	2	25.0%	6	75.0%	**8**	**100.0%**
Difficulty Supporting Family/Children			3	100.0%	**3**	**100.0%**
Emergency Funds	3	50.0%	3	50.0%	**6**	**100.0%**
Financial Support	5	31.3%	11	68.8%	**16**	**100.0%**
Food	10	19.6%	41	80.4%	**51**	**100.0%**
General FH/Financial Sit.	3	12.0%	22	88.0%	**25**	**100.0%**
Heating/Cooling	5	22.7%	17	77.3%	**22**	**100.0%**
Help from Friends/Family	3	33.3%	6	66.7%	**9**	**100.0%**
Household Repair/Maintenance	3	60.0%	2	40.0%	**5**	**100.0%**
Medication/Doctors/Health	2	11.8%	15	88.2%	**17**	**100.0%**
Mortgage/Rent	5	25.0%	15	75.0%	**20**	**100.0%**
Not Stated			7	100.0%	**7**	**100.0%**
Pawned/Sold	5	29.4%	12	70.6%	**17**	**100.0%**
Perceived Hardship			14	100.0%	**14**	**100.0%**
Social/Leisure	3	50.0%	3	50.0%	**6**	**100.0%**
Transport			3	100.0%	**3**	**100.0%**
Utilities	8	25.0%	24	75.0%	**32**	**100.0%**
2. Mental Health						
Depression	4	7.8%	47	92.2%	**51**	**100.0%**
General MH	6	14.0%	37	86.0%	**43**	**100.0%**
Anxiety	3	16.7%	15	83.3%	**18**	**100.0%**
Stress	2	50.0%	2	50.0%	**4**	**100.0%**
Diagnostic Measure of MH						
Yes	4	20.0%	16	80.0%	**20**	**100.0%**
No	11	11.5%	85	88.5%	**96**	**100.0%**
3. Controls						
Demographics						
Yes	14	14.6%	82	85.4%	**96**	**100.0%**
No	1	5.0%	19	95.0%	**20**	**100.0%**
Mental Health						
Yes	7	20.0%	28	80.0%	**35**	**100.0%**
No	8	9.9%	73	90.1%	**81**	**100.0%**
SES						
Yes	15	15.3%	83	84.7%	**98**	**100.0%**
No			18	100.0%	**18**	**100.0%**
Demographics + MH						

Yes	6	18.8%	26	81.3%	**32**	**100.0%**
No	9	10.7%	75	89.3%	**84**	**100.0%**
Demographics + MH + SES						
Yes	6	21.4%	22	78.6%	**28**	**100.0%**
No	9	10.2%	79	89.8%	**88**	**100.0%**

Discussion

General Findings

Over the past three decades, a large and growing body of evidence has highlighted the impact of socioeconomic disadvantage on numerous health outcomes, including mental health (Allen et al., 2014; Kirkbride et al., 2024; Marmot et al., 2010). In particular, the experience of financial hardship – 'being excluded from minimally accepted standards of living due to insufficient resources' (Whelan, 1993) – has demonstrated especially severe and immediate impacts on mental health. This is evidenced in several studies showing hardship experience to be more strongly associated with mental health than related measures of socioeconomic position such as low income, unemployment, or living in a disadvantaged neighbourhood (Butterworth, Olesen, et al., 2012; Foulds et al., 2014; Lorant et al., 2007).

Research assessing the relationship between financial hardship experience and mental health is characterised by considerable variability. This is evident in the research questions posed, and the diverse contexts in which studies are undertaken. In turn, this has led to substantial variation in the way different studies undertake analysis, model confounding variables, measure key health outcomes, and how the experience of financial hardship is operationalised. Given this, the broad aim of this review was to systematically curate, quantify and evaluate the nature of the current evidence examining the association between financial hardship and mental health, within studies employing a longitudinal design. Additionally, this review aimed to assess sources of heterogeneity within this relationship, associated with sample, design, and the methodological characteristics of included studies. Restricting this review to assessments using longitudinal data and longitudinal analytic techniques was important, to enable a greater understanding of the temporal dynamics between financial hardship experience and mental health, and to move beyond more commonly assessed cross-sectional associations.

Preluding a detailed discussion of specific study findings, two broad, and interrelated, themes emerged. Firstly, as anticipated this review identified extensive heterogeneity between all included studies. This diversity was most evident in the analytic approaches employed, the ways in which financial hardship was operationalised and assessed, the measures used to assess mental health, and the types of research questions that were evaluated. Secondly, despite this variation, the experience of financial hardship was overwhelmingly, and consistently associated with poorer mental health. All bivariate assessments, and 87.1% of multivariate assessments demonstrated a significant association between the experience of financial hardship and reduced mental health. This relationship was robust to variations in publication year, country of origin, survey/dataset analysed, sample features, methodological characteristics, analytic approach, financial hardship measure, mental health measure, and confounders controlled for in assessed models. While the diversity of approaches somewhat limited study synthesis, the independence of the relationship from methodological factors provides compelling evidence attesting to the potent impact of hardship experience on mental health.

Detailed Findings

Study Outcomes

A total of 116 multivariate assessments of the relationship between financial hardship and mental health were conducted across the 94 included studies. Of these, 101 assessments (87.1%) demonstrated a significant association.

Of the 15 assessments that did not demonstrate a multivariate association between financial hardship experience and poorer mental health, the majority came from studies comprising samples of less than 3000 participants, and with a smaller proportion of males to females. However, variation in the outcome of multivariate analyses demonstrated little dependence on sample age range, publication year, survey/dataset used, and survey setting. Furthermore, the outcome of multivariate analyses was also largely independent of the country where assessment took place. Though, an exception to this broad trend was found for studies conducted within the United Kingdom. Eight of the 18 assessments conducted in the United Kingdom did not demonstrate hardship experience to be associated with significantly reduced mental health. This result proved the only exception to a broad trend of results demonstrating little dependence on study characteristics. Nonetheless, these eight assessments represent over half (53.3%) of the 15 multivariate assessments that did not find a significant relationship between experiencing financial hardship and mental health. Closer inspection reveals that they came from four studies (Dunn et al., 2008; Richardson et al., 2017; Skapinakis et al., 2006; Steptoe et al., 2020) – one of which contained three assessments alone (Richardson et al., 2017) – analysing data from 2000 to 2014, and ranging in sample size from 454 to 2,761 participants. Two of the assessments utilised the 2000 Psychiatric Morbidity Survey, two used the Whitehall II survey, one used the Southampton Women's Survey (SWS), and three assessments (all in the Richardson et al., 2017 paper) came from an unnamed dataset. A common feature of these studies was their examination of baseline hardship on *subsequent* mental health outcomes. In the study by Steptoe and colleagues (2020), baseline hardship was associated with later mental health in models that did not include baseline mental health. However, this effect did not remain significant in models that adjusted for baseline mental health. Similarly, the study by Skapinakis and colleagues (2006) assessed baseline levels of financial hardship experience and stratified models according to baseline mental health status. Amongst individuals who did not have a mental health disorder at baseline, financial hardship experience was associated with disorder at follow-up. However, amongst individuals who had a mental health disorder at baseline, financial hardship experience was not associated with disorder at follow-up, regardless of whether baseline mental health was controlled for. This aligns with existing evidence assessing within-person changes in financial hardship and mental health over time, that has demonstrated the experience of hardship to have an immediate detrimental effect on mental health (Kiely et al., 2015; Lahelma et al., 2006; Lorant et al., 2007). This may explain why the effect of hardship is not as strong in studies using prospective modelling, or controlling for baseline levels of mental health.

A greater proportion of studies that made use of nationally representative surveys demonstrated a significant association between financial hardship experience and reduced mental health, than studies that did not. Subsequent analysis revealed that samples used within studies utilising data from nationally representative surveys were, on average, substantially larger than the samples used within studies that did not use data from nationally representative surveys. As noted above, the majority of assessments that did not demonstrate a significant multivariate association between financial hardship experience and mental health came from studies comprising samples of less than 3000 participants. Thus, this finding may simply reflect the fact that larger samples afford additional statistical power to detect significant associations. Additionally, studies using nationally representative surveys generally assessed financial hardship and mental health at the same time, as opposed to prospectively. Thus, these studies would have been better equipped to detect the aforementioned, immediate detrimental impacts of hardship on mental health.

Characteristics of financial hardship measures

The measures used to assess the experience of financial hardship varied extensively. This may reflect longstanding idiosyncrasies associated with assessing socioeconomic disadvantage via material privation, as opposed to more tightly defined income-based measures (such as relative and absolute poverty), or discrete indirect assessments of socioeconomic position such as educational attainment or occupational class. As highlighted by Butterworth & Crosier in 2005, there is no universally agreed upon definition of what constitutes financial hardship, no agreement on how to measure it, nor which domains of privation to include, nor whether to use individual items or multi-item/multi-dimensional scales. In the case of multi-item/multi-domain scales, there also remains no consensus on whether items should be simply summed, or differentially weighted to reflect the seriousness of their impact. The numerous ways in which financial hardship was measured across studies within this review attests to this; highlighting that two decades on, a unified definition and measurement approach remains elusive.

This review considered five different aspects of measures used to assess financial hardship: (1) Whether the measure assessed an individual's global 'perception' of having experienced hardship, or whether it inquired about the experience of 'specific' privations; (2) Whether the measure was operationalised using individual items to assess specific privations, a multi-item scale, or a question that inquired about an individual's general financial position; (3) The total number of hardship items a study/measure included; (4) The total number of distinct hardship domains a study/measure included; and (5) The specific hardship domains (or constructs) assessed within each study/measure. The majority of studies in this review (n = 62) used a financial hardship measure that assessed the experience of specific deprivations – such as "in the last 12 months, I could not pay electricity, gas or telephone bills on time" or "in the last 12 months I went without meals" (Crowe et al., 2016). Additionally, the majority of studies (n = 49) made use of a multi-item scale to assess hardship. Studies that assessed individual items of hardship most commonly only used one item and only assessed one distinct domain of hardship. The majority of multi-item scale measures of hardship comprised two to seven items and assessed one to four distinct domains of hardship. Finally, food-based insecurity or deprivation (with respect to quantity, quality, or variety) due to a lack of money was the most frequently assessed domain of hardship across the 94 included studies (n = 42), followed by difficulty paying utility bills (n = 24), and an inability to adequately heat or cool one's home (n = 17).

Outcomes with respect to financial hardship measures

Variation in the outcome of multivariate analyses was stable across several dimensions of the measures used to assess financial hardship. A slightly smaller proportion of assessments made using measures that assessed the experience of *specific* privations demonstrated a significant association between financial hardship experience and reduced mental health, than studies that used measures assessing *perceived* deprivation. This may reflect the increased precision of measures that directly inquire about whether a particular privation has occurred or not, as opposed to measures that inquire about the general state of one's finances. It is possible that a greater proportion of respondents may affirm a question inquiring about whether their general financial situation has been 'difficult', compared to a similar question inquiring about whether they have experienced specific privations. Principally, the threshold for affirming whether general difficulties have been experienced is intuitively lower than that for the experience of discreet privations. Moreover, what constitutes general financial difficulties can also be interpreted much more broadly than experiencing deprivation of a specific good. Given this, it is possible that measures based on perceptions of hardship or reports of general financial position inflate the association with mental health due to being more prone to bias. For example, individuals experiencing negative affect may be inclined to report their financial situation as being worse than individuals of a more positive disposition. Additionally, this may also reflect perceived deprivation as being more salient and impactful upon mental health than actual deprivation, particularly in cases where a particular item of privation may not have a significantly detrimental impact upon mental health. This finding would align with an extensive literature highlighting the association between subjective social status and health (Euteneuer, 2014). This work draws on evidence from both experimental animal studies and human research, emphasising the pernicious effects on health of perceiving oneself to be of 'low' relative social status in comparison to peers or other reference groups. For example, Singh-Manoux and colleagues (2005) found that subjective perceptions of socioeconomic status were a better predictor of scores on the physical and mental health components of the SF-36, the General Health Questionnaire (GHQ), and self-rated health assessments, than objective socioeconomic status measures. Similarly, Sakurai et al. (2010) found that subjective social status was a stronger predictor of psychological distress than traditional measures of socioeconomic status within a Japanese population. This finding has also been replicated amongst North American and European populations (Mishra & Carleton, 2015; Theodossiou & Zangelidis, 2009).

Potential heterogeneity was also assessed with respect to whether financial hardship was measured using a multi-item scale, individual item measures, or using a general financial question. Study outcomes were largely independent of this delineation. However, a slightly smaller proportion of assessments demonstrated a significant association between financial hardship experience and poorer mental health where a multi-item scale was used, compared to a question inquiring about one's general financial situation. All assessments made using an individual item measure of financial hardship demonstrated a significant association between hardship experience and poorer mental health. It is possible this result is due to unmeasured idiosyncratic factors that do not have anything to do with how the financial hardship measure was implemented. Nonetheless, it is curious that a smaller proportion of assessments using multi-item scales demonstrated the expected association than assessments using questions inquiring about an individual's financial situation or individual hardship items. The key benefits of using multi-item hardship scales over individual items, are (1) to account for the array of privations people may experience, and (2) to reduce confounding associated with personal preferences or lifestyle choices. By using multiple indicators of hardship, a multi-item scale, encompassing various domains of hardship, isolates elements of deprivation from individual taste, differences in resource allocation, and perceived significance or need of particular goods (Butterworth & Crosier, 2005). Moreover, the key benefit of using a multi-item scale over questions inquiring about one's 'general' financial situation, is the direct assessment of whether a particular range of basic necessities have been forgone or not due to a lack of resources. Given this, it is surprising that the expected association occurred in a smaller proportion of assessments comprising multi-item scale hardship measures, than individual item, and general financial question modalities. Given the lack of agreement surrounding what defines hardship, and therefore which items of privation multi-item hardship scales comprise, it is possible that some scales contain items that do not necessarily impact upon mental health. Moreover, the broader classification of hardship encompassed within multi-item scales, may include individuals with relatively modest financial difficulties (along with those experiencing severe financial problems), which in turn would reduce the overall observed association with mental health.

Finally, multivariate outcomes were assessed with respect to the individual constructs comprising multi and individual item measures of hardship. Again, multivariate outcomes did not differ markedly according to this dimension. However, a larger proportion of measures containing the constructs of 'emergency funds' (related to an individual's ability to raise a specific amount of money in the case of an emergency), ‘household repair/maintenance’ (insufficient money to complete necessary repair, replacement or maintenance of essential household items) and ‘social/leisure’ (insufficient money to participate in social/leisure activities) did not demonstrate a significant multivariate association with poorer mental health, than other assessed constructs. It is noteworthy that while these constructs appeared in several financial hardship measures, they do not necessarily represent absolute elemental necessities, particularly compared to food, housing, clothes or medication/healthcare access.

Outcomes with respect to assessed confounders

Outcomes of multivariate analyses were also largely independent of modelled controls. While assessments that controlled for confounding were slightly less likely to demonstrate an association between financial hardship and poorer mental health, than assessments that did not, the vast majority of multivariate models remained statistically significant. Specifically, 85.4% of assessments that controlled for demography, 80.0% of assessments that controlled for pre-existing mental health, and 84.7% of assessments that controlled for socioeconomic factors demonstrated a statistically significant association between financial hardship and poorer mental health. Moreover, 81.3% of assessments that controlled for demography *and* pre-existing mental health, and 78.6% of assessments that controlled for demography, pre-existing mental health *and* socioeconomic factors demonstrated a statistically significant association between financial hardship and poorer mental health. Again, this finding attests to the strength of the assessed relationship. Particularly given that it remains significant after adjustment for socioeconomic and demographic factors associated with reductions in mental health.

Limitations

There were several limitations to this review. Firstly, publication bias – the propensity of studies containing positive findings, compared to null findings, being published (Dwan et al., 2013) – may lead to an overestimation of the strength and consistency of the association between financial hardship and mental health. Additionally, this review only included papers published in English. This was reflected in the preponderance of studies utilising samples from the UK, USA, and Australia, or from other high income developed countries. Given this, important studies published in languages other than English would not have been included. In turn, this may preclude an understanding of the focal relationship in both lower and middle income countries, limiting the generalisability of the review findings. This review was also limited to peer reviewed published studies and did not include an assessment of grey literature, increasing the chance of publication bias. Finally, article searches were only undertaken within five databases (PubMed, Scopus, Medline, Embase, and PsycINFO). Whilst this is not an exhaustive list, it does contain some of the most commonly searched health based literature databases. Overall, the quality of included studies was high, though punctuated by substantial heterogeneity, particularly with respect to sample composition, study design, methodology, and measures used to assess financial hardship. In part, this heterogeneity was an artefact of the broad search and inclusion criteria applied at the early stages of the review. This decision was made with the aim of reviewing as comprehensive a body of relevant research as possible. However, the trade-off was that this limited study comparability. More specifically, this heterogeneity presented an impediment to aggregating study results systematically using a meta-analytic approach. While it would have been highly desirable to present a summary of effect sizes, given the vast differences between the measures used to assess financial hardship and the analytic approaches employed, effect sizes would have been pooled over very small n's. Given this, a narrative review approach was chosen. This represents both a limitation of the current work, and an opportunity for future research to attempt a systematic cataloguing of effect sizes pertaining to the longitudinal relationship between financial hardship and mental health.

Three studies received a quality score of less than 70 percent. This was largely driven by the absence of identifiable strategies to deal with confounders, follow-up being incomplete and/or no reasons given for loss to follow-up, no identifiable strategies used to address incomplete follow-up, failure to use an appropriate statistical analysis, or the study subjects and/or setting not being described in sufficient detail.

Future Research

This systematic review focused specifically on research that assessed the *longitudinal* relationship between financial hardship experience and mental health. However, the majority of included studies only used up to four waves of data, and only spanned up to five years in length. Additional research using more waves, across a wider time frame, would provide greater insight into the long term impact of financial hardship experience on mental health. More specifically, this would aid in determining whether hardship experience has broad, long term impacts on mental health, whether its impact is more immediate and temporally constrained, or whether the severity of its impact varies across the life course. Similarly, research that captures a wider view of the life course would enable a nuanced understanding of the long term mental health of individuals who experience differing hardship trajectories, such as those who have recently experienced hardship, those who experience 'one-off' moments of hardship, and those whose life course is punctuated by the experience of recurrent or chronic deprivation. Additionally, further research that leverages long term longitudinal datasets could assess whether the risk associated with experiencing financial hardship, or specific aspects of hardship, has changed over time. Taking this a step further, future work could also assess whether the risks associated with hardship experience have significantly changed over time for specific age, sex, or other sociodemographic groups.

Building on this, it would be germane to assess the extent to which differing hardship trajectories are characterised by the clustering of related social determinants, such as low education, low income, unemployment, or poorer neighbourhood conditions. Furthermore, research across a wider time frame, that captures the dynamic nature of change between childhood, adolescence and later life, would provide insight into how the psychological impacts of deprivation manifest over different stages of life, and whether exposure to hardship at different ages is associated with varying risk profiles. For example, research by Almeida and colleagues (2011) has shown how the experience of disadvantage early in life can modify the risk of poor mental health throughout the entire life course. Specifically, early life adversity has been shown to impede development, cause psychological stress, and subsequently limit access to educational and employment opportunities. Similarly, there exists evidence to suggest that the impact to mental health of disadvantage experienced in early life may not manifest fully until later life (Barr et al., 2012; Power et al., 2002), and that the benefits of higher socioeconomic status in later life may do little to compensate for the risks associated with being born into disadvantage (Präg & Richards, 2019).

Given the vast majority of included studies demonstrated a very clear and consistent longitudinal relationship between hardship experience and poorer mental health it seems pertinent for future research to move beyond oft replicated associative analyses between health and commonly used markers of socioeconomic status (such as education, income, or wealth), and instead focus on eliciting the precise mechanistic pathways explaining *why* financial hardship and lower socioeconomic status has such a strong relationship with poorer mental health. A range of studies have demonstrated that financial hardship provides a superior estimation of the association between socioeconomic status and mental health compared to measures of educational outcomes, employment status, income, wealth, and area-level disadvantage (Butterworth et al., 2012; Foulds et al., 2014; Lorant et al., 2007). These studies locate hardship as a proximal determinant of broader socioeconomic constructs, suggesting that it may play a critical role in mediating much of the association between other aspects of class and social position. Thus, future longitudinal research should systematically examine the extent to which financial hardship is mediating or moderating the relationship between mental health and more commonly assessed measures of socioeconomic position.

Another outcome of this review was identifying the extensive variation in how the experience of financial hardship has been measured and operationalised. As has been noted already, there is no universal agreement on how to best measure financial hardship. In part, this may be a difficult undertaking, given cultural differences in what is deemed deprivation, and societal disparities in wealth, and socioeconomic development. Nonetheless, it is apparent that further work could pursue the development of validated financial hardship measures applicable across different societal and cultural contexts.

Conclusion

The current review has shown financial hardship to be a potent risk factor for mental health. Furthermore, the evidence from this review confirms findings from individual studies that have shown financial hardship to be a stronger correlate of mental health than other, more commonly assessed, markers of socioeconomic position such as income, unemployment, and area-level disadvantage (Butterworth et al., 2012; Kiely et al., 2015).

These results suggest that identifying and addressing the material disadvantage experienced by the most vulnerable members of a society may substantially improve population mental health. However, continuing to improve our understanding of the distinct mechanisms and pathways through which financial hardship and socioeconomic disadvantage impacts mental health will have important implications for intervention and policy choices. Identifying key factors that lead to the onset, and continuity, of hardship will be instrumental in designing initiatives that can reduce a populations exposure to material deprivation, and mitigating its impact where it occurs. For example, if improving educational outcomes is identified as the most efficacious mechanism for interrupting the onset of hardship, and in turn, improving long term mental health outcomes, then investment in public education may be crucial. Conversely, if hardship experienced in the early-life environment is a key driver of poorer mental health across the entire life course, then investment that enables reduced familial exposure to deprivation may be most incisive policy to action.

Finally, it is also important to recognise that hardship occurs in a broader social, economic, and political context. By focusing on measures of financial hardship, this review has highlighted the critical importance of proximal adverse material circumstances. However, these conditions are a reflection of the broader socioeconomic milieu. Reducing the impact of hardship on mental health will require action at both individual and societal levels – particularly to ensure that improvements to population mental health are enduring. This means finding ways to reduce the direct impact of hardship on mental health, while advancing thoughtful policy solutions that address the broader socioeconomic conditions in which hardship and other proximal risk factors occur.

Chapter 3 - The Prevalence and Correlates of Financial Hardship in Australia – 2001 to 2023

Abstract

Background: The systematic review presented in the previous chapter demonstrated a robust and consistent positive longitudinal association between financial hardship experience and poorer mental health. Given this, there exists a need for (1) accurate and up-to-date epidemiological estimates of financial hardship prevalence, and (2) an evaluation of the strength of its association with mental health and key sociodemographic correlates.

Aims: This study aimed to estimate the prevalence of financial hardship within Australia from 2001-2023, assess the strength of its relationship with key sociodemographic and health correlates, and examine how the association between sex and age with financial hardship has changed over time.

Methods: This study analysed 23 waves of the HILDA survey, comprising 33,607 individuals and 319,965 observations. Financial hardship was assessed using an established measure comprising two components – cashflow problems and deprivation. Weighted prevalences were estimated and mixed-effects logistic regression models (univariable, multivariable, and interaction models) were used to assess correlates of, and temporal trends in, financial hardship.

Results: Between 2001 and 2023 declines were observed in the prevalence of financial hardship (29.3% - 18.0%), cashflow problems (26.4% - 15.1%) and deprivation (12.7% - 7.6%). The most prevalent forms of hardship were not being able to pay electricity, gas or telephone bills on time, and asking for financial help from friends or family. The odds of experiencing both cashflow problems and deprivation were highest amongst individuals reporting poor mental health. Higher odds of cashflow problems were also associated with being female, aged 20-29 years old, being born between 1970-1989, and having a year 12 education and being in the lowest income quintile. Factors associated with deprivation were broadly similar, along with higher odds amongst unemployed respondents, those residing in areas of greatest area-level disadvantage, and those reporting very poor levels of physical functioning. Declines in the probability of experiencing cashflow problems over time were similar for males and females, but more pronounced among younger age groups. Conversely,

while declines in the probability of experiencing deprivation over time were observed amongst males, a slight increase was observed for females and 15-19 year-olds.

Conclusion: These results highlight the risk that financial hardship poses to population mental health, that it is sensitive to macro-economic shocks, and is most prevalent amongst socioeconomically disadvantaged and psychologically vulnerable Australians.

Introduction

Background

As detailed in the introduction to this thesis, decades of research have confirmed that socioeconomic disadvantage is one of the strongest and most consistent correlates of poor mental health. Whilst this broad concept encompasses several dimensions of an individual's socioeconomic position in society, it has demonstrated consistently strong associations with poor mental health, whether measured with respect to income, wealth, level of educational attainment, employment status, occupational class, or the neighbourhood in which one resides (Ahn et al., 2019; Allen et al., 2014; Araya, 2003; Bambra & Eikemo, 2008; Benach & Muntaner, 2007; Enticott et al., 2016; Ettman et al., 2020; Halpern, 1995; Isaacs et al., 2018; Kendall et al., 2019; Kessler & Cleary, 1980; Lorant et al., 2007; Lund et al., 2010; Montgomery, 1999).

Moreover, the preceding chapters have demonstrated that socioeconomic disadvantage can also be assessed with respect to the experience of financial hardship – an outcome-based approach that overcomes limitations associated with traditional income and wealth-based assessments, by evaluating the *direct consequences* of insufficient financial resources (Bray, 2001; Butterworth, Olesen, et al., 2012; Butterworth & Crosier, 2005; Foulds et al., 2014). The systematic review presented in the previous chapter overwhelmingly confirmed a highly robust and consistent positive longitudinal association between financial hardship experience and poorer mental health.

This chapter expands upon these foundations, by presenting current epidemiological estimates of financial hardship prevalence, along with quantifying its association with mental health and key sociodemographic correlates using a nationally representative sample of the Australian population.

Economic Context

Assessing the prevalence, distribution, and correlates of socioeconomic disadvantage is vital for understanding national wellbeing, and for informing effective social policy. This is especially germane in light of major global events over the past 25 years that have advanced substantial economic disruption, including the 2008 financial crisis, the economic fallout of the COVID-19 pandemic, ongoing geopolitical instability, and the recent diffusion of advanced automation technologies. Mirroring trends observed in other advanced economies, Australia has also been impacted by these global disruptions. Despite nearly three decades of uninterrupted GDP growth, the Australian economy experienced a substantial slowdown following the COVID-19 pandemic (Ergas & Branigan, 2023). Moreover, Australia's long-term macroeconomic resilience has obscured pronounced domestic changes that have had a significant impact on household living standards. This is exemplified most notably in the substantial rise in the cost of housing, which has consistently outpaced both wage growth and CPI inflation (Bradbury & Saunders, 2022; Morris, 2023; Pawson et al., 2020). This trend has entrenched existing income and wealth divides with respect to housing tenure, and contributed to an increase in poverty rates when housing costs are accounted for (Saunders et al., 2022a)[29]. Consequently, for many Australians, income gains over the last three decades have barely offset rising housing costs (Saunders et al., 2022a). Additionally, these events have coincided with persistently high inflation and increases in the Reserve Bank of Australia (RBA) cash rate[30] in the years following the COVID-19 pandemic (ABS, 2024a; Tsiaplias & Wang, 2023).

For several decades many economists have argued that increases in overall national GDP improve the living standards of *all* socioeconomic groups in a society (Berg & Ostry, 2011; Dollar & Kraay, 2002; Gwartney et al., 1999; King & Levine, 1993; Kuznets, 1955). However, counterarguments have highlighted that GDP increases are not evenly distributed, in part due to the propensity for economic growth and inequality to coincide. As a result, there are many people in society who do not necessarily experience any tangible improvements to their living conditions (Atkinson, 2015; Campos-Vazquez et al., 2017; Kwon & Salcido, 2019; Piketty, 2014; Saunders et al., 2022a).

Given the qualitative impact of these changes to the Australian economy, traditional measures of societal and individual economic wellbeing (such as relative income poverty, or overall national GDP) may not be fully capturing the real deprivation experienced by many Australian households. Thus, measures of financial hardship, which directly assess instances where socially perceived necessities have been forgone, serve as a crucial complement to traditional indicators of socioeconomic wellbeing. Financial hardship measures capture

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[29] Specifically, Saunders et al., (2022a) use the term 'After housing costs poverty' (AHC) to define this measure.
[30] The RBA 'cash rate' is the benchmark interest rate that sets the lending rate between financial institutions in Australia. It influences all other interest rates, including mortgage and deposit rates, and has an indirect effect on inflation, employment and exchange rates (Reserve Bank of Australia, 2025a, 2025b).

dimensions of financial pressure beyond income and wealth, and in turn assist in providing a comprehensive understanding of living standards.

Given this, the present study uses a measure of financial hardship to assess the experience of socioeconomic disadvantage. Comprehensively understanding the prevalence, distribution, and correlates of financial hardship, and particularly its association with mental health, is a vital complement to prevailing research that has assessed socioeconomic disadvantage and mental health outcomes in Australia with respect to traditional income and wealth-based indicators. Moreover, this approach provides an essential foundation for further examination of important longitudinal relationships between financial hardship, including its trajectory over time, with outcomes such as mental health.

Financial Hardship

The measure of financial hardship used within this study is a seven-item scale constructed from a broader set of questions developed by the Australian Bureau of Statistics (ABS). These items were informed by prior research examining living standards within Australia, and formally introduced in the 1998-99 Household Expenditure Survey (Bray, 2001). The seven items collectively evaluate whether a household could not afford to pay for a range of socially perceived essential goods and services – such as utilities, housing expenses, heating costs, or food – along with whether they have been compelled to pawn belongings, or seek financial help from friends, family, or welfare organisations as a result of inadequate financial resources.

Butterworth and Crosier (2005) used the term *financial hardship* to define this specific collection of items, in order to emphasise the link between limited financial resources and the experience of hardship. Throughout this chapter, this term will be used when referring to this specific seven-item outcome scale.

Conceptually, the items comprising this financial hardship scale are similar to the dimension of deprivation Whelan and colleagues defined as *basic lifestyle deprivation* (Whelan, 1993; Whelan et al., 2001). They also align with Beverly's (2001) conception of *material hardship* – which she defined with respect to inadequate consumption of very basic goods and services – and *financial hardship* – having difficulty paying rent/mortgage or utilities. Importantly, this seven-item financial hardship measure is focused on capturing the objective indicators of material need, as opposed to the social dimensions of exclusion or the subjective elements of financial satisfaction or perceived prosperity (Butterworth & Crosier, 2005).

Furthermore, factor analysis has shown that these seven items reflect two correlated sub-dimensions. Using data from the 1998–99 Household Expenditure Survey, Bray (2001) identified a robust three-factor solution. Three items pertaining to not being able to pay utilities, housing costs, and asking for financial help from friends and family, loaded onto a single factor. Bray termed this factor "cashflow problems" given it reflected household budgetary challenges, as opposed to direct deprivation. The remaining four items pertaining to pawning items, being unable to heat one's home, going without meals, and asking for help from welfare/community organisations loaded onto a second factor. Bray termed this "hardship", given it represented deprivation arising due to limited financial resources. A third factor, *missing out*, consisted of six items reflecting constraints on lifestyle and leisure; these items do not contribute to the seven-item measure of interest here. Nonetheless, subsequent work by Kiely et al. (2015) demonstrated that both dimensions of the two-factor solution (cashflow problems and deprivation) were significantly associated with poor mental health. Related analyses have also shown that a unidimensional model also provides an adequate fit for these seven items (Butterworth & Crosier, 2005).

This specific seven-item measure of financial hardship has been widely used within Australian research over the past two decades to examine its relationship with various health outcomes (Butterworth et al., 2009; Butterworth, Olesen, et al., 2012; Crowe et al., 2016; Kiely et al., 2015). Using data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, Bray (2024) estimated that in 2022 approximately 18.2% of the Australian population aged 15 years and over had experienced at least one of the seven hardship items. Notably, the majority of these individuals (14.6%) were not classified as experiencing relative income poverty – highlighting the aforementioned imperfect relationship between material deprivation and income.

In particular, studies have repeatedly highlighted that this measure of financial hardship has a strong and independent relationship with mental health, and that it mediates the relationship between traditional measures of social position and mental health (Butterworth et al., 2009; Butterworth, Olesen, et al., 2012). Extending upon this, work by Kiely et al. (2015) showed that in both between and within-person analyses, current financial hardship – rather than past hardship – shared the strongest association with concurrent reductions in mental health. Similarly, Crowe et al. (2016) applied the same seven-item measure and found that financial hardship significantly attenuated the association between unemployment and poor mental health.

Aims

The aim of this study is to use nationally representative longitudinal data to (1) estimate the overall prevalence of financial hardship in Australia; (2) assess the strength of the association between financial hardship and a range of sociodemographic characteristics and health factors; and (3) evaluate how the strength of the relationship between both sex, and age with cashflow problems and deprivation has changed over time.

Methods

Data

The analysis for this study used data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. A detailed explanation of the HILDA survey can be found in the General Introduction (Chapter 1) under the section titled *Data Sources*.

Sample

The sample analysed in this study uses the first twenty-three waves of the HILDA Survey, spanning 2001 to 2023. It was restricted to all participants who completed the Self-Completion Questionnaire (SCQ) in each wave. Additionally, wave 10 (in 2010) of the HILDA Survey did not assess financial hardship. Data from this wave was excluded from all analyses. This provided a wave 1 sample comprising 7,245 households and 13,058 responding individuals. Using the SCQ responding person weights, this yields an estimated weighted population of 14,923,779 in wave 1. Table 8 provides the number of households, individuals (n) and estimated weighted population (Weighted n) comprising the analytic sample each year. Importantly, the SCQ responding person weights results in a weighted sample aligned to annual Australian Bureau of Statistics (ABS) population benchmarks. The final analytic sample comprised 33,607 individuals (48.2% male / 51.8% female) who contributed a total of 319,965 observations over 23 waves. The weighted sample was used to estimate the prevalence of financial hardship from 2001 to 2023 in Australia.

Table 8

Analytic sample details[31]

Year	Households	n	Estimated Pop.
2001	7,245	13,058	14,923,779
2002	6,824	12,130	15,133,844
2003	6,616	11,747	15,347,574
2004	6,496	11,397	15,552,868
2005	6,481	11,465	15,786,018
2006	6,543	11,688	16,057,442
2007	6,349	11,381	16,379,640
2008	6,245	11,193	16,750,326
2009	6,406	11,563	17,105,835
2011	8,468	15,366	17,641,853
2012	8,504	15,389	17,955,273
2013	8,437	15,360	18,257,488
2014	8,561	15,595	18,529,494
2015	8,567	15,513	18,803,944
2016	8,962	16,253	19,120,187
2017	8,961	16,140	19,451,566
2018	8,792	15,887	19,781,106
2019	8,915	16,082	20,108,254
2020	8,955	15,676	20,298,824
2021	8,828	15,299	20,373,462
2022	8,497	14,814	20,791,738
2023	8,486	14,917	21,437,023

[31] Note: Sample details for 2010 were not included in this table as financial hardship data was not collected.

Measures

The analysis in this study used measures of *sex*, *age*, and *birth cohort*, *time block*, *education*, *employment status*, *income*, *area-level socioeconomic disadvantage*, *residing with parents*, *financial hardship*, *cashflow problems*, *deprivation*, *physical functioning*, and *mental health*. Details pertaining to how each of these items have been assessed and defined can be found in the General Introduction (Chapter 1) under the section titled *Data Sources*.

Analysis

All analyses were conducted using R version 4.5.0 (R Core Team, 2025). Sample characteristics were assessed descriptively across all waves of data from 2001 to 2023. Population, and prevalence estimates of financial hardship were calculated using the 'srvyr' package (Freedman Ellis & Schneider, 2016) with data weighted to adjust for selection, non-response and attrition over time. Given the key variables are drawn from the SCQ, this analysis used the SCQ responding person weights. All mixed-effects logistic regression models were estimated using unweighted data, as R does not currently support random-effects regression modelling with survey weights.

Prevalence of Financial Hardship in Australia

The prevalence of financial hardship in Australia from 2001 to 2023 was assessed across multiple dimensions. Firstly, the overall weighted prevalence of financial hardship in Australia from 2001 to 2023 was estimated. Secondly, the weighted prevalence of the seven individual items comprising the overall financial hardship measure was estimated. Thirdly, weighted prevalence estimates of financial hardship were disaggregated by levels of key sociodemographic factors to identify sub-populations at increased risk of experiencing financial hardship. This included sex, age, birth cohort, SEIFA quintile, education level, employment status, income quintile, (SF-36) physical functioning decile, (SF-36) mental health decile, and whether residing with a parent. Finally, the overall weighted prevalence of cashflow problems and deprivation was assessed to ascertain whether the pattern of results observed for the overall financial hardship construct were consistent across both of its correlated subdimensions.

Correlates of Financial Hardship in Australia

To assess the strength of the relationship between key sociodemographic correlates and financial hardship, cashflow problems and deprivation, a series of mixed-effects logistic regression models were estimated. Univariable models were estimated to assess the unadjusted association between each sociodemographic factor and financial hardship and its two subdimensions (cashflow problems, and deprivation). Multivariable models were also estimated to simultaneously adjust for all key sociodemographic factors in their relationship to financial hardship, cashflow problems and deprivation. Finally, models containing an interaction term were used to assess how the strength of the relationship between both sex, and age has changed over time with cashflow problems, and deprivation. A two-stage process was undertaken to assess whether the inclusion of interaction terms and covariates improved model fit. First, baseline models (containing sex or age as predictors) were compared to models including sex-by-time or age-by-time interaction terms. Secondly, these interaction models were compared to models that further adjusted for additional covariates. Model fit was assessed using AIC, BIC, log-likelihood, and chi-square tests. An individual-level random intercept was included in all logistic regression models to account for the correlation between repeated observations from the same respondents, and to capture unobserved heterogeneity in baseline (i.e., Wave 1) levels of financial hardship.

Sensitivity Analyses

Sensitivity analyses were conducted to test the robustness of the prevalence estimates to panel conditioning (Bach, 2021). The prevalence of hardship, cashflow problems, and deprivation were re-estimated after removing participants' first wave of data.

Results

Overall prevalence of financial hardship in Australia

The estimated prevalence of financial hardship among Australians aged 15 and older, from 2001 to 2023 is shown in Figure 3. Over the course of the study period, the prevalence of financial hardship changed from 29.3% in 2001 (95% CI = 28.4, 30.2) to 21.6% in 2023 (95% CI = 20.6, 22.6). Moreover, notable fluctuations occurred within this timespan. Principally, the most pronounced reduction in the prevalence of financial hardship occurred from 2001 to 2008, where a decline of more than 10 percentage points was observed, from 29.3% (95% CI = 28.4, 30.2) to 18.5% (95% CI = 17.5, 19.4). This decline was followed by an increase between 2008 and 2011, where prevalence rose to 23.8% (95% CI = 22.8, 24.8). From 2011, the prevalence of financial hardship steadily declined, before reaching its lowest point of 18.0% (95% CI = 17.1, 18.8) in 2017. This was followed by a period of relative stability until 2022, before rising sharply in 2023 to 21.6% (95% CI = 20.6, 22.6).

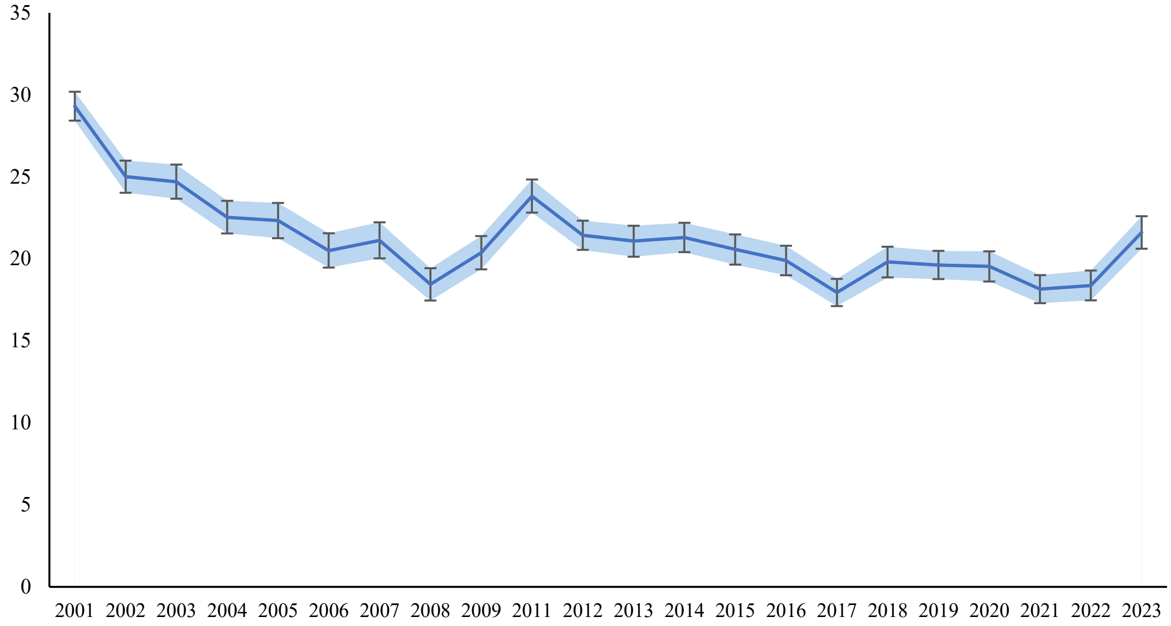


Figure 3
Estimated Prevalence of Financial Hardship in Australia from 2001 to 2023

Figure 4 presents the estimated prevalence of cashflow problems and deprivation – the two sub-dimensions of financial hardship – within Australians aged 15 and older, spanning 2001 to 2023.

Broadly speaking, the prevalence of both cashflow problems and deprivation follow a similar trajectory to the prevalence of overall financial hardship, displaying similar annual peaks and troughs. Overall, the prevalence of deprivation is substantially lower than cashflow problems across the entire study period.

Specifically, the prevalence of cashflow problems peaked in 2001 at 26.4% (95% CI = 25.5, 27.2), and reached its lowest point in 2021 at 15.1% (95% CI = 14.3, 15.9). A persistent decline in prevalence to 16.7% (95% CI = 15.6, 17.5) occurred between 2001 and 2008, before markedly increasing to 20.7% (95% CI = 19.7, 21.6) in 2011. From 2011 to 2021, the prevalence of cashflow problems gradually declined, before evidencing an upward trend since 2021.

The prevalence of deprivation peaked in 2001 at 12.7% (95% CI = 12.1, 13.4) and reached its lowest point of 7.6% (95% CI = 6.9, 8.2) in 2006. Akin to the trend observed in financial hardship and cashflow problems, the prevalence of deprivation increased sharply from 2008, reaching 10.9% (95% CI = 10.2, 11.6) in 2011. From 2012 to 2021, rates of deprivation stabilised between 9.4% and 10.6%. However, from 2021 deprivation has trended upwards, reaching 12.0% (95 CI = 11.2-12.7) in 2023 – comparable to the level observed in 2001.

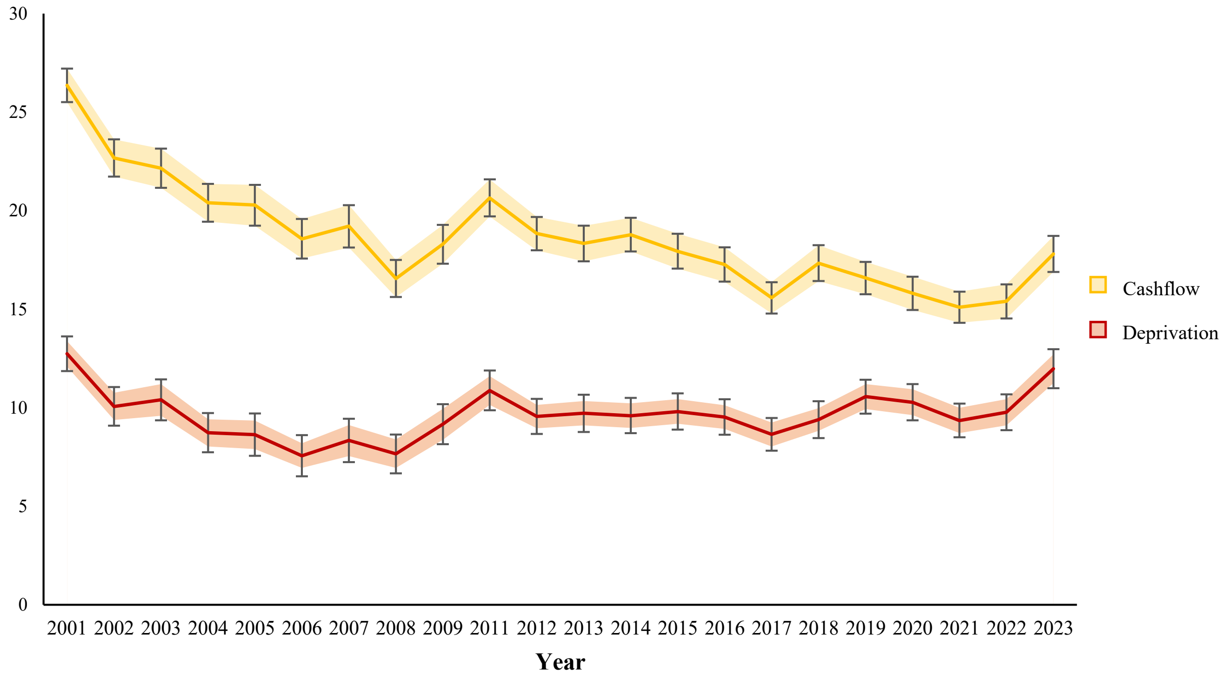


Figure 4

Estimated Prevalence of Cashflow Problems and Deprivation in Australia from 2001 to 2023

Figure 5 presents the estimated prevalence of each individual item constituting the full financial hardship measure among Australians aged 15 and older, from 2001 to 2023. Tabulated figures, including n's, estimated prevalences and corresponding 95% confidence intervals are provided in Appendix B.5

Across the entire study period, the most prevalent forms of hardship were not being able to pay electricity, gas, or telephone bills on time (FH1), and asking for financial help from friends or family (FH2), both components of the cashflow problems dimension. Notably, both items followed a similar trajectory across the assessed timespan and evidenced the largest decrease in prevalence of the seven measures. Rates of FH1 and FH2 both peaked in 2001 at 18.3% (95% CI = 17.6, 19.1) and 16.7% (95% CI = 16.0, 17.5) respectively. FH1 declined to a low of 9.8% (95% CI = 8.9, 10.1) in 2022, while FH2 reached its lowest point of 8.5% (95% CI = 7.9, 9.1) in 2020.

The prevalence of the remaining five financial hardship items has consistently stayed below ten percent. For example, the prevalence of not being able to pay mortgage or rent on time (FH3) ranged from 8.8% to 5.4%, while pawning or selling something (FH4) ranged from 6.3% to 3.7%. Similarly, the prevalence of being unable to heat one's home (FH5) ranged from 4.3% to 1.7%, going without meals (FH6) ranged from 5.2% to 2.9%, and asking for help from welfare/community organisations (FH7) ranged from 5.3% to 3.1%. Overall, each of these items showed evidence of very slight declines during the early 2000's, before stabilising until 2021. The prevalence of all seven items has evidenced signs of an upward trend since 2021/2022.

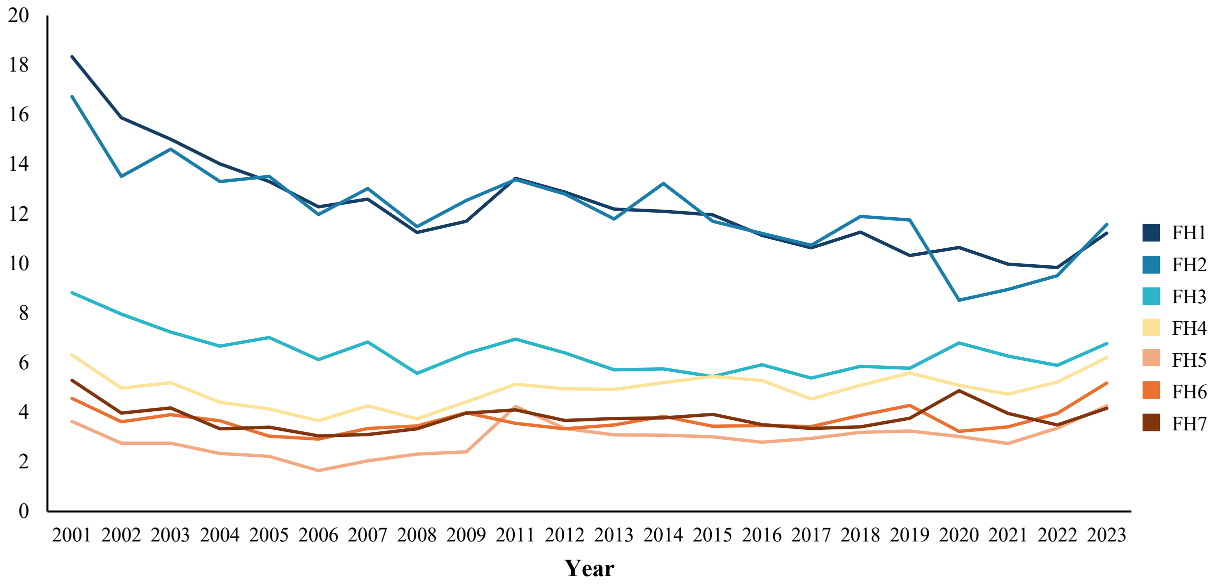


Figure 5

Estimated Prevalence of each individual financial hardship item in Australia from 2001 to 2023

Assessing the strength of the association between key sociodemographic and health correlates of cashflow problems and deprivation

Summary

Table 9 presents pooled prevalence, univariable odds ratios, and 95% confidence intervals for the likelihood of experiencing cashflow problems and deprivation, according to key sociodemographic and health correlates. Building upon this, Table 10 presents the corresponding multivariable odds ratios and 95% confidence intervals for experiencing cashflow problems and deprivation, with all key sociodemographic and health correlates modelled together.

Overall, significant associations with cashflow problems and deprivation were evident across all assessed variables in the univariable and multivariable analyses. Individuals with greater socioeconomic disadvantage and poorer health had consistently higher odds of experiencing both outcomes. In particular, very poor mental health was associated with substantially elevated odds of experiencing both cashflow problems and deprivation. However, this analysis also revealed distinct sociodemographic patterns in the likelihood of experiencing cashflow problems and deprivation.

Cashflow problems were strongly associated with sex, age, birth cohort, education, income, and mental health. Specifically, individuals who experienced cashflow problems were more likely to be female, aged 20-29, born between 1970-1989, hold Year 12 as their highest level of education, belong to the lowest quintile of household income, and to have very poor mental health (lowest decile, 0-10). Furthermore, these associations held in the multivariable analysis that modelled all correlates together.

The profile for deprivation shared broad similarity with that of cashflow problems, particularly with respect to age, birth cohort, and mental health. However, the experience of deprivation was also strongly associated with SEIFA, employment status, and physical functioning. In the univariable analysis, individuals who experienced deprivation were more likely to be aged 20-29, born between 1970-1989, score low on physical functioning, have very poor mental health (decile 0-10), be unemployed, reside in areas of greatest disadvantage (SEIFA quintile 1), and belong to the lowest quintile of household income. This profile remained largely robust in the corresponding multivariable analysis that assessed all correlates in concert. However, in the multivariable analysis, females were significantly less likely to experience deprivation than males.

What follows is a more detailed description of the associations between key sociodemographic and health factors that characterise the experience of cashflow problems and deprivation.

Cashflow Problems

The prevalence of cashflow problems has consistently declined with time. In 2001-2006, the pooled prevalence was 21.7%. By 2019-2023, this figure had dropped to 16.2%. Accordingly, the odds of experiencing cashflow problems reflect this consistent decline. In the univariable analysis (Table 9) the odds of experiencing cashflow problems reduced by 29% in 2007-2012 (OR = 0.71, 95% CI = 0.68, 0.73), 46% in 2013-2018 (OR = 0.54, 95% CI = 0.52, 0.56) and 58% in 2019-2023 (OR = 0.42, 95% CI = 0.40, 0.44). This declining trend was confirmed in the multivariable analysis (Table 10), with odds reducing by 9% in 2007-2012 (OR = 0.91, 95% CI = 0.87, 0.95), 25% in 2013-2018 (OR = 0.75, 95% CI = 0.71, 0.79), and 37% in 2019-2023 (OR = 0.63, 95% CI = 0.60, 0.68).

Cashflow problems were slightly more prevalent amongst females (18.8%) than males (16.4%). In line with this, females had significantly higher odds of experiencing cashflow problems in both the univariable (OR = 1.26, 95% CI = 1.19, 1.34) and multivariable analyses (OR = 1.14, 95% CI = 1.08, 1.20) than males. A consistent age based pattern also emerged in both unadjusted and adjusted analyses. 15-19 year-olds had lower odds of experiencing cashflow problems, compared to 20-29 year olds and each successive age group above 20-29 had progressively lower odds (Table 9). In the unadjusted analysis (Table 9), 15-19 year-olds had 62% lower odds of experiencing hardship than 20-29 year-olds (OR = 0.38, 95% CI = 0.36, 0.40). This pattern of results was replicated in the multivariable analysis (Table 10) with declines in odds ranging from 29% for 30-39 year-olds (OR = 0.71, 95% CI = 0.67, 0.75) to 87% for the 70+ age group (OR = 0.13, 95% CI = 0.11, 0.15).

Individuals born between 1970-1989 reported the highest prevalence of cashflow problems (pooled prevalence = 23.84%). Accordingly, prevalence and odds (in both unadjusted and adjusted analyses) declined progressively with successively older birth cohorts. For example, the multivariable odds declined from 0.65 in the 1950-1969 cohort (95% CI = 0.50, 0.71), to 0.19 in the 1900-1929 cohort (95% CI = 0.15, 0.24). In both analyses, individuals born between 1990-2009 had lower odds of cashflow problems compared to those born in 1970-1989 (unadjusted OR = 0.56, 95% CI = 0.52, 0.61; adjusted OR = 0.62, 95% CI = 0.57, 0.68).

The pooled prevalence of cashflow problems progressively increased from 11.7% in areas of greatest advantage (SEIFA quintile 5) to 23.2% in areas of greatest disadvantage (SEIFA quintile 1). In line with this, compared to areas of greatest advantage, the univariable odds of experiencing cashflow problems steadily increased, from 1.12 in SEIFA quintile 4 (95% CI = 1.05, 1.18), to 1.71 in SEIFA quintile 1 (95% CI = 1.61, 1.82). This pattern was largely preserved in the multivariable analysis, with significantly greater odds of cashflow problems observed in SEIFA quintile 3 (OR = 1.15, 95% CI = 1.08, 1.22) to SEIFA quintile 1 (OR = 1.35, 95% CI = 1.27, 1.44).

Individuals holding postgraduate qualifications had the lowest pooled prevalence of cashflow problems (10.6%), while those having a Year 12 level of education reported the highest (20.3%). Accordingly, in comparison to postgraduate qualifications (PhD or Master's level), all lower levels of education were associated with significantly higher odds of experiencing cashflow problems in both univariable and multivariable analyses (Table 9/Table 10). For example, compared to holding postgraduate qualifications, the multivariable odds of cashflow problems were 1.3 times greater amongst individuals with undergraduate qualifications (OR = 1.30, 95% CI = 1.16, 1.46), over two times greater for those holding a diploma/vocational qualifications (OR = 2.12, 95% CI = 1.89, 2.38), and a Year 12 level of education (OR = 2.16, 95% CI = 1.92, 2.43), and 1.92 times greater for those with a Year 11 level of education (OR = 1.92, 95% CI = 1.70, 2.16).

The pooled prevalence of cashflow problems increased from 16.5% for those holding full-time employment, to 34.3% for those who were unemployed. Accordingly, the univariable odds associated with working part-time (OR = 1.27, 95% CI = 1.22, 1.32), being unemployed (OR = 2.37, 95% CI = 2.22, 2.52), and not being in the labour force (OR = 1.13, 95% CI = 1.09, 1.18), were significantly higher in comparison to full-time employment. Moreover, only modest adjustments in odds were observed across these levels of employment in the multivariable analysis. Specifically, working part-time (OR = 1.16, 95% CI = 1.12, 1.21), being unemployed (OR = 1.94, 95% CI = 1.81, 2.07), and not being in the labour force (OR = 1.21, 95% CI = 1.15, 1.26) remained associated with significantly higher odds of cashflow problems than full-time employment.

A clear gradient in the prevalence of cashflow problems was observed across household income quintiles. The pooled prevalence of cashflow problems ranged from 8.3% in the highest quintile of household income (quintile 5), to 25.8% in in the lowest (quintile 1). The corresponding univariable and multivariable odds also reflected this gradient in prevalence, with adjusted odds ranging from 1.65 in income quintile 4 (OR = 1.65, 95% CI = 1.58, 1.74), to 4.95 in quintile 1 (OR = 4.95, 95% CI = 4.66, 5.25) (Table 10).

The pooled prevalence of cashflow problems increased slightly with poorer physical functioning, ranging from 15.8% in the top decile of health, to 23.0% in the second lowest (11-20). The corresponding univariable odds of experiencing cashflow problems reflected this. Compared to the highest decile of physical functioning (91–100), the odds of experiencing cashflow problems progressively increased from 1.11 in the 81-90 decile of physical functioning (OR = 1.11, 95% CI = 1.07, 1.16), to 1.27 in the 11-20 decile (OR = 1.27, 95% CI = 1.15, 1.40). This pattern remained in the multivariable analysis, however odds at each decile of physical functioning were higher. Specifically, the multivariable odds ranged from 1.25 in the 81-90 decile (95% CI = 1.20, 1.30), to 1.61 in the 11-20 decile (95% CI = 1.46, 1.78).

The pooled prevalence of cashflow problems increased substantially as mental health declined. The prevalence ranged from 8.7% in the top decile, to 46.5% in the second lowest decile (11-20). Both the univariable and multivariable odds of experiencing cashflow problems reflected this. For example, compared to those in highest decile of mental health (91-100), the multivariable odds of experiencing cashflow problems increased from 1.39 in the 81-90 decile (95% CI = 1.31, 1.46), to 6.11 times greater in the lowest decile (95% CI = 4.93, 7.58).

Deprivation

Unlike cashflow problems, the pooled prevalence of deprivation increased slightly over time, rising from 9.7% in 2001-2006, to 10.4% in 2019-2023. In the univariable analysis, the odds of deprivation consistently remained around 10% lower than in 2001-2006. However, the multivariable analysis revealed an upward trend, with adjusted odds rising from 1.12 (95% CI = 1.06, 1.18) in 2007-2012, to 1.18 (95% CI = 1.09, 1.28) in 2019-2023.

Deprivation was slightly more prevalent amongst females (9.5%) than males (9.1%). No significant differences in the odds of experiencing deprivation were observed in the univariable analysis, however females exhibited significantly lower odds of experiencing deprivation in the multivariable analysis (OR = 0.83, 95% CI = 0.78, 0.89). This result was explored further using a series of eleven stepwise mixed-effects logistic regression models with random intercepts – as detailed in Appendix B.9 – to ascertain how the assessed sociodemographic and health variables contributed to females having lower odds in the multivariable analysis, despite similar odds in the univariable analysis. This analysis found that the female odds of deprivation became significantly lower than males, upon the inclusion of employment status. Specifically, model 1.6 in Appendix B.9 – which included sex, age, birth cohort, time, SEIFA, and employment status – showed the female odds of deprivation to be 13% lower than males (OR = 0.87, 95% CI = 0.80, 0.93). Moreover, this finding was replicated within all subsequent models (1.7, 1.9, 1.10, and 1.11) that adjusted for employment status.

Prevalence of deprivation declined markedly with age, falling from 12.6% in 20-29 year-olds, to 4.3% in the 70+ age group. The univariable analysis demonstrated that all age groups had significantly lower odds of deprivation than 20-29 year-olds, (Table 9) and these results were confirmed in the multivariable analysis, with odds significantly declining from 0.85 (95% CI = 0.79, 0.91) in 30-39 year-olds, to 0.18 (95% CI = 0.15, 0.22) in those aged 70+ (Table 10).

Rates of deprivation also decreased with older birth cohorts. The prevalence declined from 11.6% for individuals born between 1970-1989 to 3.7% for those born from 1900-1929. Accordingly, the univariable analysis showed a progressive decline in odds with older birth cohorts. These results were robust in the multivariable analysis, with odds declining from 0.66 in the 1950-1969 cohort (95% CI = 0.59, 0.73) to 0.2 in the 1900-1929 cohort (95% CI = 0.15, 0.27).

The prevalence of deprivation increased from 5.1% in areas of greatest socioeconomic advantage (SEIFA quintile 5) to 15.0% in areas of greatest disadvantage (SEIFA quintile 1). In line with this, the univariable analysis demonstrated a progressive increase in odds with greater area-level disadvantage. This pattern was confirmed in the multivariable analysis, with odds ranging from 1.08 (1.01-1.17) in SEIFA quintile 4 to 1.55 (95% CI = 1.43, 1.67) in SEIFA quintile 1.

Rates of deprivation also varied by level of education, ranging from 4.3% for individuals with postgraduate qualifications, to 10.9% for those with a Year 11 education. Compared to postgraduate qualifications, the odds of experiencing deprivation in the univariable analysis increased from 1.55 in undergraduates (95% CI = 1.31, 1.84) to 4.03 for those with a Year 12 education (95% CI = 3.39, 4.78). In contrast, the odds of experiencing deprivation by education level in the multivariable models revealed a slightly different pattern. The highest odds were observed for individuals with a diploma or vocational qualifications (OR = 1.97, 95% CI = 1.68, 2.29), followed by those with a Year 11 education (OR = 1.81, 95% CI = 1.55, 2.13), those with a Year 12 education (OR = 1.72, 95% CI = 1.47, 2.01), and those with an undergraduate degree (OR = 1.17, 95% CI = 1.00, 1.37).

Deprivation was markedly more prevalent amongst people who were unemployed (24.7%) than those not in the labour force (11.5%), working part-time (9.0%), or working full-time (6.5%). This was reflected in the pattern of univariable odds and remained robust in the multivariable analysis. Being unemployed (OR = 3.54, 95% CI = 3.28, 3.81), not in the labour force (OR = 1.97, 95% CI = 1.86, 2.09), or working part-time (OR = 1.53, 95% CI = 1.45, 1.61) were all associated with significantly higher odds of deprivation, compared to holding full-time employment.

The prevalence of deprivation increased from 3.2% for those in the highest quintile of household income (quintile 5), to 18.6% for those in the lowest (quintile 1). This variation was reflected in the univariable analysis and confirmed in the multivariable modelling with odd ranging from 1.61 (95% CI = 1.51, 1.73) to 6.0 (95% CI = 5.55, 6.49) for those in household income quintiles 4 and 1 respectively.

A progressive increase in the prevalence of deprivation was observed as physical functioning declined. The prevalence of deprivation ranged from 7.1% in the top decile of physical functioning to 16.6% in the second lowest (decile 11-20). Univariable and multivariable analysis confirmed increasing odds of deprivation with lower physical functioning. Specifically, the multivariable odds increased from 1.28 in the 81-90 decile (95% CI = 1.22, 1.35), to 1.96 in the 11-20 decile (95% CI = 1.75, 2.20).

Similarly, rates of deprivation increased markedly with poorer mental health. Specifically, the prevalence of deprivation increased from 3.3% in the top decile of mental health (90-100), to 45.7% in the lowest decile (0-10). Accordingly, in comparison to the highest decile of mental health, a substantial increase in the associated univariable odds was also observed, increasing from 1.44 in the 81-90 decile (95% CI = 1.34, 1.56), to 21.5 in the lowest decile of mental health (95% CI = 17.1, 27.1). The multivariable analysis confirmed these results, with substantially higher odds of deprivation observed as mental health declined. Compared to those in highest decile of mental health (91-100), the multivariable odds of experiencing deprivation increased from 1.33 in the 81-90 decile (95% CI = 1.24, 1.44), to 13.5 times greater in the lowest decile (95% CI = 10.70, 17.0).

Table 9
Pooled Prevalence (23 waves) and univariable odds of experiencing Cashflow Problems, and Deprivation by key sociodemographic factors

* Bold denotes statistical significance

	Cashflow Problems			Deprivation		
Characteristic	**Prev**	**OR**	**95% CI**	**Prev**	**OR**	**95% CI**
Time Block						
01-06	21.68	—	—	9.65	—	—
07-12	15.58	0.71	**0.68, 0.73**	7.61	0.90	**0.86, 0.95**
13-18	17.52	0.54	**0.52, 0.56**	9.45	0.89	**0.85, 0.93**
19-23	16.15	0.42	**0.40, 0.44**	10.40	0.91	**0.87, 0.96**
Sex						
Male	16.43	—	—	9.08	—	—
Female	18.79	1.26	**1.19, 1.34**	9.45	1.04	0.95, 1.12
Age Category						
15-19	12.46	0.38	**0.36, 0.40**	7.76	0.55	**0.52, 0.59**
20-29	25.42	—	—	12.60	—	—
30-39	24.25	0.60	**0.58, 0.63**	11.85	0.77	**0.73, 0.81**
40-49	20.89	0.38	**0.36, 0.40**	10.39	0.54	**0.51, 0.58**
50-59	14.71	0.19	**0.18, 0.21**	8.22	0.40	**0.37, 0.43**
60-69	9.67	0.09	**0.09, 0.10**	6.23	0.26	**0.24, 0.28**
70+	6.85	0.07	**0.06, 0.07**	4.34	0.18	**0.17, 0.21**
Birth Cohort						
1900-1929	6.53	0.09	**0.07, 0.11**	3.71	0.13	**0.10, 0.17**
1930-1949	8.39	0.12	**0.11, 0.13**	5.15	0.19	**0.17, 0.22**
1950-1969	16.88	0.40	**0.37, 0.43**	8.73	0.46	**0.41, 0.51**
1970-1989	23.84	—	—	11.58	—	—
1990-2009	17.39	0.56	**0.52, 0.61**	10.78	1.00	0.90, 1.11
SEIFA						
5 (Greatest Advantage)	11.67	—	—	5.06	—	—
4	14.92	1.12	**1.05, 1.18**	7.04	1.29	**1.20, 1.40**
3	17.73	1.28	**1.21, 1.36**	9.12	1.57	**1.45, 1.69**
2	21.67	1.48	**1.39, 1.57**	11.05	1.80	**1.66, 1.94**
1	23.20	1.71	**1.61, 1.82**	14.98	2.34	**2.16, 2.54**
Education						
Postgrad	10.62	—	—	4.27	—	—
Undergrad	12.86	2.11	**1.88, 2.38**	5.48	1.55	**1.31, 1.84**
Diploma/Vocational	19.95	3.79	**3.36, 4.27**	10.78	3.48	**2.94, 4.13**
Year 12	20.32	5.75	**5.10, 6.50**	9.78	4.03	**3.39, 4.78**
Year 11 or below	18.28	3.18	**2.82, 3.58**	10.88	3.09	**2.61, 3.66**
Employment						
Full Time	16.52	—	—	6.46	—	—
Part Time	18.83	1.27	**1.22, 1.32**	8.97	1.73	**1.64, 1.81**
Unemployed	34.31	2.37	**2.22, 2.52**	24.66	4.57	**4.25, 4.91**
Not in labour force	16.65	1.13	**1.09, 1.18**	11.49	2.21	**2.10, 2.33**
Income Quintile (Household)						
5 (Highest)	8.26	—	—	3.23	—	—
4	13.75	1.87	**1.78, 1.96**	5.70	1.78	**1.66, 1.91**
3	20.02	3.06	**2.91, 3.21**	9.03	2.90	**2.70, 3.11**
2	24.02	4.46	**4.24, 4.69**	13.58	4.76	**4.43, 5.10**
1	25.75	5.43	**5.14, 5.74**	18.57	7.13	**6.62, 7.69**
Physical Functioning (SF-36)						
91-100	15.84	—	—	7.12	—	—
81-90	17.67	1.11	**1.07, 1.16**	8.61	1.28	**1.21, 1.35**
71-80	17.96	1.08	**1.02, 1.13**	10.05	1.43	**1.34, 1.53**
61-70	19.99	1.16	**1.09, 1.23**	12.27	1.62	**1.50, 1.74**
51-60	20.74	1.19	**1.11, 1.28**	13.34	1.69	**1.56, 1.84**
41-50	22.40	1.20	**1.12, 1.29**	15.08	1.90	**1.75, 2.07**

31-40	22.41	1.28	**1.18, 1.38**	14.75	1.98	**1.80, 2.18**
21-30	22.13	1.28	**1.17, 1.39**	16.04	2.06	**1.87, 2.28**
11-20	22.99	1.27	**1.15, 1.40**	16.64	2.16	**1.93, 2.41**
0-10	21.90	1.09	0.99, 1.20	15.05	1.92	**1.72, 2.15**
Mental Health (SF-36)						
91-100	8.71	—	**—**	3.31	—	**—**
81-90	12.20	1.50	**1.43, 1.58**	4.55	1.44	**1.34, 1.56**
71-80	15.75	2.02	**1.92, 2.13**	6.94	2.26	**2.10, 2.43**
61-70	19.75	2.59	**2.45, 2.75**	10.09	3.22	**2.98, 3.49**
51-60	24.70	3.20	**3.02, 3.39**	14.65	4.39	**4.06, 4.75**
41-50	29.09	3.98	**3.72, 4.27**	19.29	6.15	**5.63, 6.72**
31-40	32.86	4.71	**4.38, 5.07**	23.21	7.59	**6.91, 8.32**
21-30	39.09	5.69	**5.12, 6.31**	29.78	10.10	**8.98, 11.5**
11-20	46.46	7.14	**6.31, 8.08**	38.30	13.70	**12.0, 15.8**
0-10	44.49	8.11	**6.57, 10.0**	45.68	21.50	**17.1, 27.1**

Table 10

Multivariable odds of experiencing Cashflow Problems and Deprivation by key sociodemographic factors

* Bold denotes statistical significance

	Cashflow Problems		Deprivation	
Characteristic	**OR**	**95% CI**	**OR**	**95% CI**
Time Block				
01-06	—	—	—	—
07-12	0.91	**0.88, 0.95**	1.12	**1.06, 1.18**
13-18	0.75	**0.71, 0.79**	1.10	**1.03, 1.18**
19-23	0.63	**0.60, 0.68**	1.18	**1.09, 1.28**
Sex				
Male	—	—	—	—
Female	1.14	**1.08, 1.20**	0.83	**0.78, 0.89**
Age Category				
15-19	0.28	**0.26, 0.29**	0.36	**0.34, 0.39**
20-29	—	—	—	—
30-39	0.71	**0.67, 0.75**	0.85	**0.79, 0.91**
40-49	0.52	**0.49, 0.57**	0.66	**0.60, 0.73**
50-59	0.35	**0.31, 0.38**	0.53	**0.46, 0.60**
60-69	0.18	**0.15, 0.20**	0.29	**0.24, 0.34**
70+	0.13	**0.11, 0.15**	0.18	**0.15, 0.22**
Birth Cohort				
1900-1929	0.19	**0.15, 0.24**	0.20	**0.15, 0.27**
1930-1949	0.30	**0.26, 0.34**	0.32	**0.26, 0.38**
1950-1969	0.65	**0.60, 0.71**	0.66	**0.59, 0.73**
1970-1989	—	—	—	—
1990-2009	0.62	**0.57, 0.68**	0.89	**0.80, 0.98**
SEIFA				
5 (Greatest Advantage)	—	—	—	—
4	1.04	0.98, 1.10	1.08	**1.01, 1.17**
3	1.15	**1.08, 1.22**	1.23	**1.14, 1.33**
2	1.23	**1.16, 1.30**	1.28	**1.19, 1.39**
1	1.35	**1.27, 1.44**	1.55	**1.43, 1.67**
Education				
Postgrad	—	—	—	—
Undergrad	1.30	**1.16, 1.46**	1.17	**1.00, 1.37**
Diploma/Vocational	2.12	**1.89, 2.38**	1.97	**1.68, 2.29**
Year 12	2.16	**1.92, 2.43**	1.72	**1.47, 2.01**
Year 11 or below	1.92	**1.70, 2.16**	1.81	**1.55, 2.13**
Employment				
Full Time	—	—	—	—
Part Time	1.16	**1.12, 1.21**	1.53	**1.45, 1.61**
Unemployed	1.94	**1.81, 2.07**	3.54	**3.28, 3.81**
Not in labour force	1.21	**1.15, 1.26**	1.97	**1.86, 2.09**
Income Quintile				
5 (Highest)	—	—	—	—
4	1.65	**1.58, 1.74**	1.61	**1.51, 1.73**
3	2.58	**2.46, 2.71**	2.52	**2.35, 2.70**
2	3.79	**3.60, 4.00**	3.97	**3.70, 4.27**
1	4.95	**4.66, 5.25**	6.00	**5.55, 6.49**
Physical Functioning (SF-36)				
91-100	—	—	—	—
81-90	1.25	**1.20, 1.30**	1.28	**1.22, 1.35**
71-80	1.29	**1.22, 1.36**	1.41	**1.32, 1.51**
61-70	1.42	**1.33, 1.51**	1.54	**1.43, 1.67**
51-60	1.45	**1.35, 1.56**	1.56	**1.43, 1.70**
41-50	1.42	**1.32, 1.53**	1.68	**1.54, 1.83**
31-40	1.58	**1.45, 1.72**	1.82	**1.66, 2.01**

21-30	1.59	**1.46, 1.74**	1.89	**1.70, 2.09**
11-20	1.61	**1.46, 1.78**	1.96	**1.75, 2.20**
0-10	1.34	**1.21, 1.48**	1.67	**1.49, 1.88**
Mental Health (SF-36)				
91-100	—	**—**	—	**—**
81-90	1.39	**1.31, 1.46**	1.33	**1.24, 1.44**
71-80	1.80	**1.71, 1.89**	1.96	**1.82, 2.10**
61-70	2.27	**2.14, 2.40**	2.68	**2.47, 2.90**
51-60	2.75	**2.59, 2.91**	3.45	**3.20, 3.73**
41-50	3.33	**3.10, 3.57**	4.55	**4.16, 4.98**
31-40	3.88	**3.60, 4.18**	5.45	**4.96, 5.98**
21-30	4.55	**4.09, 5.07**	7.02	**6.20, 7.94**
11-20	5.63	**4.96, 6.39**	8.92	**7.76, 10.3**
0-10	6.11	**4.93, 7.58**	13.50	**10.7, 17.0**

Assessing the strength of the association between sex and age, with cashflow problems and deprivation, over time

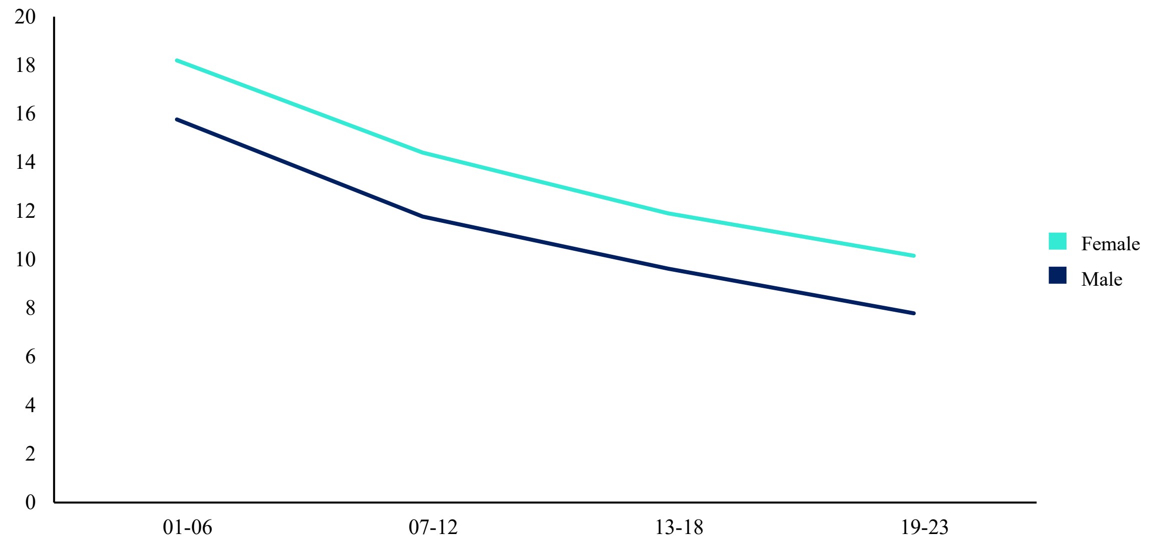
Figure 6 and Figure 7 present predicted probabilities, derived using a margins approach, to illustrate how the likelihood of experiencing cashflow problems and deprivation has evolved over time by sex and age. Summary output containing odds ratios (ORs) and 95% confidence intervals (CIs) for models (1 and 2) assessing sex by time interactions are detailed in Appendix B.6, while the corresponding output for models (3 and 4) assessing age by time interactions are detailed in Appendix B.7. Model fit comparison statistics (detailed in Appendix B.8) indicated that the inclusion of interaction terms and covariates significantly improved model fit. Accordingly, predicted probabilities presented below are disaggregated by sex (models 1 and 2) and age (models 3 and 4) and are derived from models that control for birth cohort and whether individuals aged 15–19 and 20–29 were residing with their parents.

Model 1 in Figure 6 presents the relationship between sex and cashflow problems over time, after adjusting for age, birth cohort, and whether 15-19 and 20-29 year-olds were residing with their parents. Both sexes demonstrated a decline over time in the probability of experiencing cashflow problems, with females consistently showing higher probability at each time point. Specifically, the probability of experiencing cashflow problems for males declined from 15.8% to 7.8% between 2001-2006 and 2019-2023, whereas for females the probability declined from 18.2% to 10.2%. The decline experienced by males was greater than females, and the relative difference widened over time. In 2001-2006, females were approximately 15.4% more likely to experience cashflow problems than males (18.2.0% vs 15.8%); by 2019-2023 this gap had widened to approximately 30.4% (10.2% vs. 7.8%).

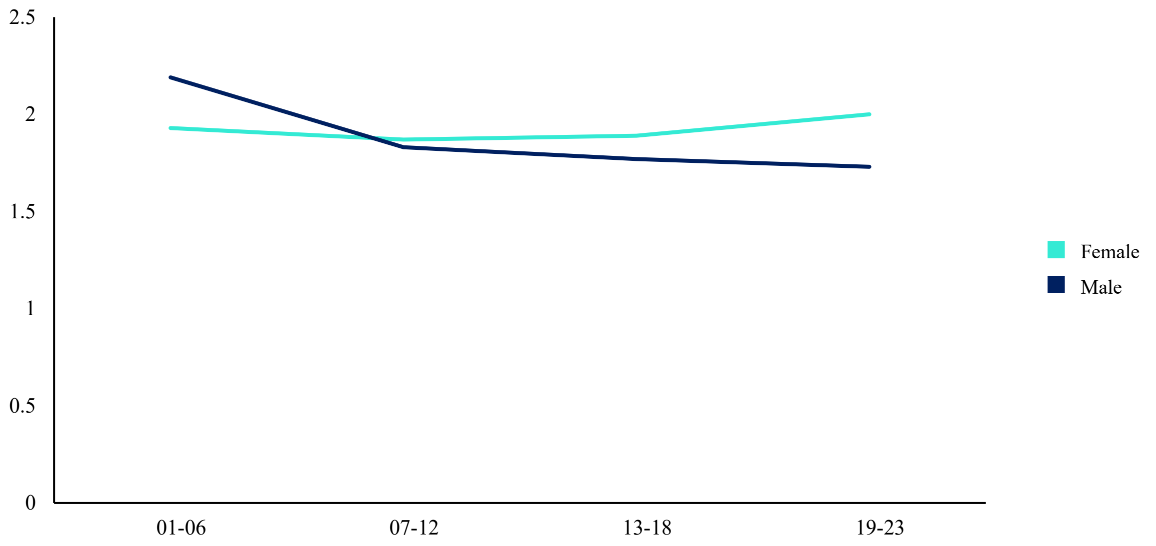
Model 2 in Figure 6 displays the relationship between sex and deprivation over time, after adjusting for age, birth cohort, and whether 15-19 and 20-29 year-olds were residing with their parents. The probability of experiencing deprivation for males, declined from 2.2% to 1.7% between 2001-2006 and 2019-2023. In contrast, the probability for females increased from 1.9% to 2% over the same period. Thus, while females were observed to be 11.9% less likely to experience deprivation than males in 2001-2006 (1.9% vs 2.2%), in 2019-2023 they were 15.6% more likely (2.0% vs 1.7%).

Model 3 in Figure 7 presents the relationship between age and cashflow problems over time, after adjustment for sex, birth cohort, and whether 15-19 and 20-29 year-olds were residing with parents. An overall declining trend of cashflow problems was observed. Declines were observed for all ages, except the 70+ group which showed a minor 0.4% increase. Declines over time were largest amongst younger ages and became less pronounced with older age groups. For example, the probability of experiencing cashflow problems in 20-29 year-olds declined from 29.7% to 11.9% between 2001-2006 and 2019-2023, while the probability for 60-69 year-olds declined from 5.8% to 3.6%. Notably, the probability for 15-19 year-olds declined from 28.7% in 2001-2006, to 15.5% in 2019-2023. The relative difference in probabilities between age groups narrowed substantially over the study period.

Model 4 in Figure 7 presents the relationship between age and deprivation over time, after adjustment for sex, birth cohort, and whether 15-19 and 20-29 year-olds are residing with parents. The probability of experiencing deprivation over time declined for respondents aged 20-29, 30-39, 40-49, and 70+. Moreover, only minimal differences between 2001-2006 and 2019-2023 were observed for 50-59 and 60-69 year-olds. However, a notable increasing trend was observed amongst 15-19 year-olds between 2013-2018 and 2019-2023, with probabilities rising from 3.5% to 4.3%. Overall, the relative difference in probability between ages 20-29 and 70+ appeared to narrow over time, whereas 15-19 year-olds increasingly diverged.

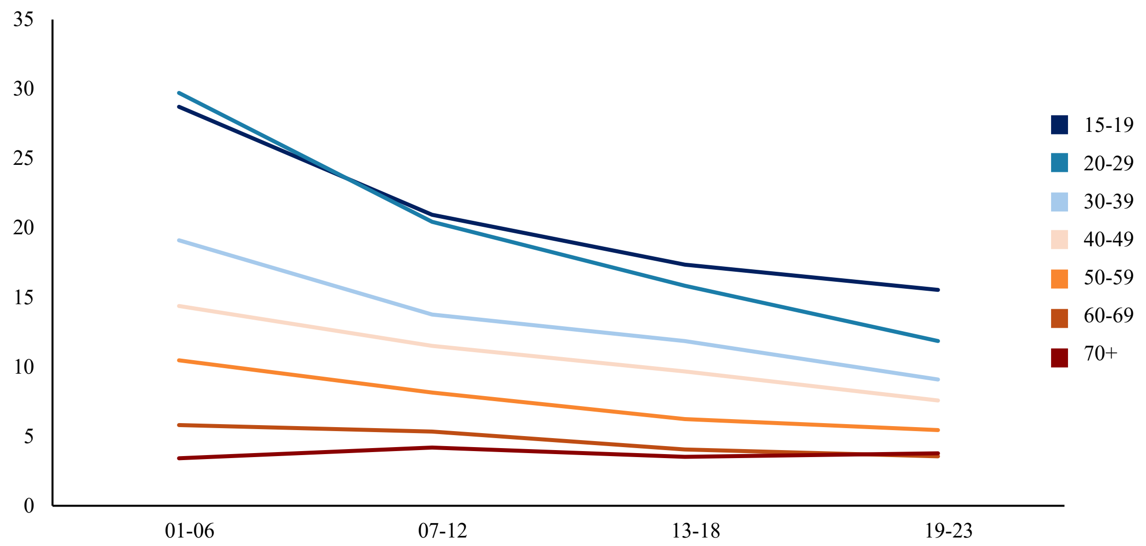


Model 1 - Cashflow Problems

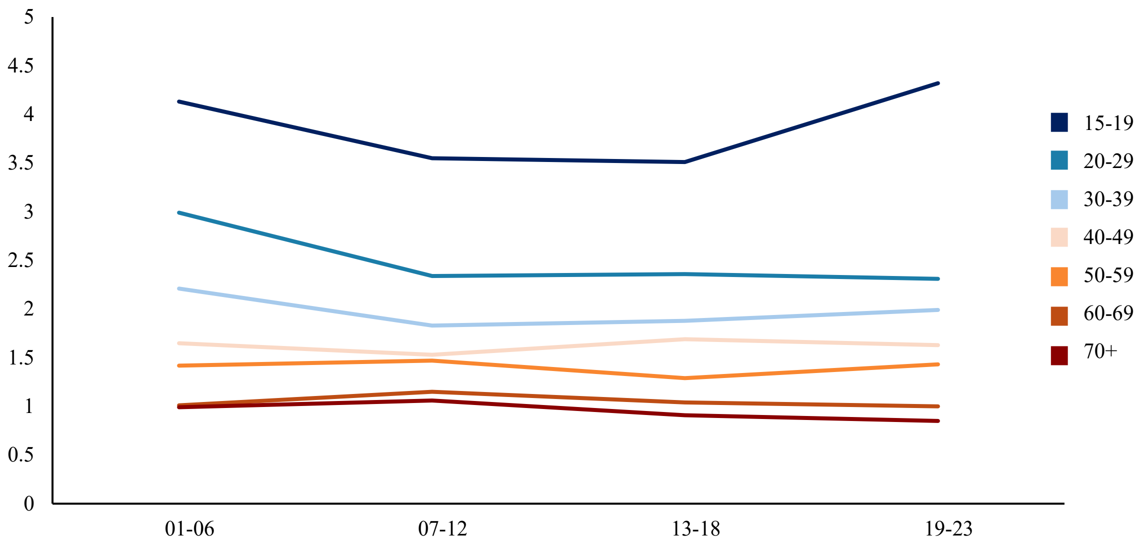


Model 2 - Deprivation

Figure 6
Predicted probability of experiencing cashflow problems and deprivation, over time, by sex
* Adjusted for age, birth cohort, and whether 15-19/20-29 year-olds are residing with their parents.



Model 3 - Cashflow Problems



Model 4 - Deprivation

Figure 7

Predicted probability of experiencing cashflow problems and deprivation, over time, by age

* Adjusted for sex, birth cohort, and whether 15-19/20-29 year-olds are residing with their parents.

Sensitivity Analysis

Sensitivity analyses were conducted to re-estimate prevalence estimates for financial hardship, cashflow problems, and deprivation after excluding respondents' first wave of participation in the HILDA Survey. The results of this sensitivity analysis are presented in Appendix B.4, and indicated that the exclusion of participants' first wave of data had no substantive impact on estimated prevalence. The re-estimated prevalence of all three outcomes followed a near identical trajectory to the main analyses, confirming the initial results.

Discussion

Summary of General Findings

The majority of studies that assess population living standards use a relative income line – typically, 50% of median equivalised household income. This chapter aimed to complement and extend this work, by using 23 waves of HILDA Survey data spanning 2001-2023 to assess the prevalence, correlates, and distribution of financial hardship – a direct, outcome-based measure of socioeconomic disadvantage. As summarised by Saunders and colleagues (2022a), while income is a 'major determinant of people's ability to meet basic needs', assessments of hardship reveal when 'living conditions are unacceptable' by the standards of the broader community. This study provides the first long-term population estimates of the prevalence of financial hardship in Australia, along with quantifying the strength of its relationship with a comprehensive suite of sociodemographic and health factors. The findings reveal several notable temporal and demographic patterns of hardship experience over the 23 year study period.

Despite declining over time, financial hardship was found to affect a substantial minority of the Australian population. While the overall trend declined from 29.3% (95% CI = 28.4, 30.2) in 2001 to 21.6% (95% CI = 20.6, 22.6) in 2023, these figures highlight that approximately 1 in 5 Australians currently experience financial hardship. Moreover, there was a clear pattern of hardship rates surging in 2008, following the Global Financial Crisis (GFC), in 2021 after the COVID-19 pandemic, and again in 2023 as the RBA cash rate and economic inflation began rising in Australia (Australian Institute of Health and Welfare, 2025b).

Analysis of the two sub-dimensions of financial hardship, revealed the prevalence of both subscales broadly mirrored the overall hardship trend, albeit with lower magnitude. Moreover, the prevalence of cashflow problems was substantially higher than the prevalence of deprivation. While the prevalence of cashflow problems has declined steadily between 2001 and 2023, the prevalence of deprivation has remained similar between these two time points. Analysis by sub-groups however, suggests that deprivation rates have even increased amongst adolescents (aged 15-19) and females. Analysis at the item-level of the scale revealed that not being able to pay electricity, gas, or telephone bills on time, and asking for financial help from friends or family were the most prevalent forms of hardship.

Lower socioeconomic groups consistently demonstrated elevated rates and higher odds of experiencing hardship. For example, a steep and persistent social gradient was observed across income quintiles – compared to households in the top income quintile, those in the lowest income quintile were approximately five times more likely to report cashflow problems and six times more likely to report deprivation. Similarly, unemployed respondents were approximately twice as likely to report cashflow problems and 3.5 times more likely to report deprivation. Those with only a year 11, year 12, or vocational education were roughly two times more likely to report both cashflow problems and deprivation, than individuals with postgraduate qualifications.

Young people (aged 20-29) and those born between 1970-1989 experienced substantially higher rates of cashflow problems and deprivation than older adults. Women consistently demonstrated higher odds of cashflow problems than men, whereas men demonstrated higher odds of experiencing deprivation once employment status was controlled for.

A gradient in the likelihood of experiencing hardship was also observed for health. Respondents' likelihood of experiencing cashflow problems and deprivation increased as physical functioning declined. Most striking however, was the strength of the relationship between hardship and mental health. Respondents in the lowest decile of mental health were over six times more likely to experience cashflow problems, and more than thirteen times likely to experience deprivation than those in the highest decile.

What follows is an interpretation of these results framed against contemporary ideas in social epidemiology, with respect to current international evidence.

Interpretation

The overall rate of financial hardship declined from 29.3% in 2001 to 21.6% in 2023. To contextualise these numbers, Bray (2024), using HILDA Survey data, estimated that relative income poverty (50% threshold) increased from 12.4% to 13.3% between 2001 and 2022. Similarly, Saunders et al. (2022) estimated a slight decline in the same income poverty rate from 9.6% in 2005-2006 to 8.0% in 2017-2018, using data from the Survey of Income and Housing (SIH). Strikingly, in further analysis that accounted for housing costs, Saunders and colleagues (2022) observed an *increase* in the relative income poverty rate from 12.3% to 12.9% over the same period[32]. Taken together, rates of financial hardship are substantially higher than rates of poverty, when measured using the traditional 50% median income threshold. This indicates that rates of socioeconomic disadvantage, when defined by the proportion of the population going without socially perceived necessities, may markedly exceed rates indicated by traditional relative income poverty thresholds.

The sharp increase in rates of hardship observed in 2008 and 2021 aligns with the economic and labour market disruption associated with the global financial crisis and the COVID-19 pandemic. Moreover, the timing also corresponds with international evidence demonstrating comparable increases in the experience of related financial stressors (such as job loss, or having difficulty paying rent), unemployment, relative poverty, objective and subjective financial hardship, and decreases in household income (Egger et al., 2021; Ettman et al., 2021; Jackson et al., 2025; Jenkins et al., 2013; Josephson et al., 2021; Kim et al., 2021; Whelan et al., 2017).

Interestingly, the prevalence of overall financial hardship masked a diverging trend between rates of cashflow problems and deprivation. Bray (2001) proposed that cashflow problems reflect a household's capacity to balance fluctuations in income and expenses, indicating situations where limited financial resources may be managed by delaying bill payments. Deprivation however, captures circumstances where a household is incapable of affording basic necessities. Given this, cashflow problems are possibly more common and less severe than the experience of absolute deprivation. However, more recent work by Bray (2024) has provided evidence to suggest that deprivation is more common amongst those classified as experiencing relative poverty. Bray (2024) investigated endorsement of the same hardship

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[32] Saunders et al., (2022) also estimated before and after housing cost relative poverty rates measured at the 60% median threshold. Both rates were markedly higher than when measured at the 50% threshold. The before housing costs relative poverty rate declined from 17.1% in 2005-2006 to 15.7% in 2017-2018, while the after housing costs relative poverty rate remained steady at around 19% during the same period.

measure items from the HILDA Survey in 2022, with respect to whether respondents were experiencing relative poverty according to the 50% median income threshold. Those in relative poverty accounted for 19.8% to 22.0% of those affirming experience of the three items comprising cashflow problems. However, endorsement of the four items comprising deprivation was much higher amongst those experiencing relative poverty, ranging from 22.3% to 33.9%. More broadly, this also highlights that the measure of financial hardship used in this study identifies a much larger proportion of the population as experiencing socioeconomic disadvantage than measures that use relative income thresholds.

Consistent with prior research from Australia, there was a more pronounced concentration of hardship within socioeconomically disadvantaged subgroups. This included those who are unemployed, who hold lower levels of education, or who reported lower household incomes (Davidson et al., 2021, 2022, 2023; Hashmi et al., 2020; Saunders et al., 2022a). For example, Hashmi and colleagues (2020) found lower socioeconomic status groups were significantly more vulnerable to experiencing life shocks (such as financial hardship) than high socioeconomic groups. Similarly, higher rates of relative and absolute poverty, financial shocks, and financial insecurity have been observed amongst lower socioeconomic groups within international social epidemiological research. For example, studies from the UK, US, and EU have all demonstrated increased rates of poverty and socioeconomic disadvantage amongst single parents, unemployed individuals, those with lower education, and individuals in poor health or with disabilities (Brady, 2023; Brady et al., 2017; Eurostat, 2025; Joseph Rowntree Foundation, 2025; Shrider & Creamer, 2023). These findings are consistent with explanations of health gradients which argue that individuals with fewer financial resources often lack the knowledge, assets, or social connections to avoid exposure to various health-related stressors, or to safeguard themselves from overly severe outcomes when momentary financial shocks do occur (Link & Phelan, 1995; Phelan et al., 2010).

This study found that young adults were particularly vulnerable to experiencing financial hardship. It is likely that this finding in part reflects the transition out of the family home, time spent engaged in tertiary study, insecure and/or part-time employment, and lower levels of savings. Nonetheless, this echoes the results of similar research conducted within Australia, albeit using different data (Tran et al., 2025), along with international studies which have reported above average poverty rates amongst teenagers and young adults (Davidson et al., 2023; Eurostat, 2025; Rahman, 2019). Concerningly, there is growing evidence that rates of relative poverty amongst younger age groups may be increasing (Rahman, 2019)[33].

The most striking finding of this analysis was the strength of the relationship between financial hardship experience and mental health. Respondents in the lowest decile of mental health had exceptionally elevated odds of experiencing both cashflow problems and deprivation. While the magnitude of these odds was surprising, the direction of this result aligns with decades of global evidence that has repeatedly demonstrated a strong and highly robust association between poor mental health and socioeconomic disadvantage (Allen et al., 2014; Braveman & Gottlieb, 2014; Compton & Shim, 2015; Kirkbride et al., 2024; Reiss, 2013). Studies in psychiatric epidemiology, carried out across varying countries and utilising a diversity of designs and methodological approaches, have repeatedly found relative and absolute poverty to be one of the strongest risk factors for poor mental health (C. M. Heflin & Iceland, 2009; Kessler & Cleary, 1980; Krieger, 2007; Lorant et al., 2007; Lund et al., 2010; McLeod & Shanahan, 1996; Ridley et al., 2020; Thomson et al., 2023; Weich & Lewis, 1998). Moreover, this finding is supported by an array of existing research that has also found a striking relationship between financial hardship experience and poor mental health (Ahnquist & Wamala, 2011; Borrescio-Higa et al., 2022; Butterworth et al., 2009; Butterworth, Olesen, et al., 2012; Foulds et al., 2014; French & Vigne, 2019; Jackson et al., 2025; Kang et al., 2021; Kiely et al., 2015; Lynch et al., 1997; Marshall et al., 2022; Mirowsky & Ross, 2001; Skapinakis et al., 2006).

The finding that cashflow problems were more common, yet deprivation shared a stronger relationship with mental health aligns with previous work by Butterworth and colleagues (2012) who used the 2007 Australian National Survey of Mental Health and Wellbeing. Research has also shown that experiencing deprivation has a greater impact on the risk of future mental health problems than income poverty; indeed, after accounting for hardship experience, income poverty did not increase the risk of experiencing mental health problems (Kiely et al., 2015). While this study did not assess individual hardship items, previous work has highlighted that going without meals – an item comprising the deprivation sub-dimension – posed the greatest risk to mental health (Butterworth et al., 2012; Kiely et al., 2015). Furthermore, by disaggregating within- and between-person hardship terms (i.e., the

[33] In the UK, relative poverty rates between older and younger age groups have increasingly diverged since the 1980's. For example, the relative poverty rate amongst pensioners has declined from over 40% in the mid 1980's to just over 15% in 2015. Over the same period however, this rate has increased from roughly 17% to over 30% for people aged under 18.

difference *between* each individual's person-mean on a particular variable versus intraindividual *within-person* changes in a person's mean level on an independent variable), Kiely et al. (2015) demonstrated (1) that individuals who had *never* experienced hardship had significantly better mental health than those who had, and (2) that the risk of poor mental health was significantly higher at the specific times when hardship was experienced.

Finally, these findings should be positioned within the broader mental health context outlined in the introduction to this thesis. In brief, an array of evidence has consistently demonstrated a steady increase in the prevalence of mental disorders within Australia over the past three decades. In contrast, the analyses presented within this chapter indicate an overall decline in the prevalence of financial hardship within Australia between 2001 and 2023. Given the strong association observed between financial hardship and mental health, this raises the question of why declines in hardship have not coincided with corresponding declines in the prevalence of mental disorders. Several explanations may account for this. Firstly, the models assessed within this chapter did not specifically examine the strength of the association between financial hardship and mental health over time. Furthermore, mental health is a complex product of numerous determinants beyond financial hardship (Figueroa et al., 2020; Kirkbride et al., 2024). Thus, declines in financial hardship may not translate into population level reduction in mental disorder where other risk factors have persisted or worsened. Trends in financial hardship are also sensitive to the indicator used and have not universally declined across all measures (Australian Bureau of Statistics, 2025; Australian Institute of Health and Welfare, 2024, 2025c). Finally, hardship may have remained concentrated amongst high-risk subgroups. Therefore, overall population-level declines in hardship may not reflect the continual burden of hardship experienced by those who are most vulnerable to poor mental health.

Strengths and Limitations

The principal strength of this study is the use of very high quality panel data. The HILDA Survey is a large, nationally representative cohort comprising over 17,000 respondents, with annual follow-up since 2001 (Watson & Wooden, 2012). Re-interview rates have remained in excess of 93 percent for the majority of survey waves. The sample used in this study comprised 33,607 unique individuals, who contributed a total of 319,965 observations over 23 waves between 2001 and 2023. Use of such a large, long-standing, national survey confers several benefits. Principally, HILDA comprises a sample that is broadly reflective of the Australian population. This allows generalisable national prevalence estimates, and population-level associations. Secondly, given the longitudinal design of the HILDA survey it contains repeated measures of financial hardship and key sociodemographic and health variables. This enables a disaggregation of cohort from period effects, and the ability to control for fixed and varying characteristics of individuals as numerous aspects of their lives change over time (such as employment, income, education, or health). Finally, the seven-item measure of financial hardship contained within HILDA has demonstrable reliability and validity, and has been used extensively in Australian social-policy research to measure outcome-based deprivation for more than two decades (Bray, 2001; Butterworth, Olesen, et al., 2012; Butterworth & Crosier, 2005; Crowe et al., 2016; Kiely et al., 2015).

Nonetheless, some limitations to this study should be noted. Firstly, the focal hardship measure, and the measures of health are self-reported. Respondents may under-report hardship experience (or poor health/mental health) due to social desirability and the stigma associated with being poor and/or in poor health (particularly mental health). Similarly, mental health was assessed using self-report as opposed to clinical diagnosis. The MHI-5 component of the SF-36 is a long-standing, validated measure of mental health (Ware et al., 1993; Ware & Sherbourne, 1992). However, it may not be as sensitive to subtle mental health disorders as an assessment conducted by a trained clinical psychologist.

Moreover, there is a chance that some respondents may have initially interpreted financial hardship (and the associated questions) differently. We attempted to control for this and panel conditioning by assessing whether excluding each respondent's first survey wave altered prevalence estimates for cashflow problems and deprivation – particularly given that there was evidence of relatively high rates of hardship in the first wave of HILDA (2001) and in the wave coinciding with the sample top-up (2011). However, this sensitivity analysis did not identify distinct differences in the rates of either outcome from their initial estimates.

It is worth noting, that the association between cashflow problems and deprivation experience with poor mental health was incredibly strong. However, the analysis conducted within this study is unable to infer causality. It is possible that this relationship is bi-directional, and/or confounded by unmeasured variables (such as familial, personality, cultural, and genetic factors). Research using approaches designed to disentangle directionality, such as random-intercept cross-lagged panel models, are needed to discern whether hardship experience predicts poor mental health, or whether experiencing poor mental health leads to increased hardship experience. Furthermore, the temporality of the two measures used to assess this specific association should be noted. The financial hardship measure used in HILDA asks respondents to affirm whether they have experienced each item of deprivation *over the past 12 months*. In contrast, the SF-36 assesses mental health over the *preceding 4 weeks*. Prior research has shown this relationship to be highly contemporaneous (Butterworth et al., 2009; Butterworth, Olesen, et al., 2012; Kiely et al., 2015; Witteveen & Velthorst, 2020). This raises the possibility that the 12-month interval used in the HILDA survey may (at least in some cases) be too long to capture the precise temporal nature of the relationship between hardship and mental health. Given this, the association may be stronger if measured over a shorter time frame such as a month or weeks. More broadly, given HILDA is an annual survey, within-year dynamics are masked. In turn, this precludes a precise assessment of whether hardship precedes or follows changes in mental health, differentiation of one-off hardship shocks from multiple hardship spells in the same year, and short-term hardship from more sustained, chronic events. Finally, we chose to categorise people as experiencing hardship, cashflow problems, and/or deprivation if they affirmed experiencing at least one item in each construct. This binary approach maximises sensitivity, but sacrifices nuance, and may obscure the varying impact of different hardship profiles.

As with any long-standing panel study, the HILDA survey is subject to attrition. Prevalence estimates adjusted for dropout using appropriate sample weights. However, due to existing limitations in the 'srvyr' R statistical package it was not possible to incorporate weights when conducting random-effects regression analyses. Consequently, this may have attenuated some associations, particularly if those respondents who experience hardship are more likely to drop out. Similarly, the HILDA survey does not contain a measure of financial hardship in wave 10 (2010) which creates a minor gap in the time series – preventing a more precise examination of hardship trends immediately following the GFC and prior to the subsequent economic recovery. Finally, the HILDA Survey under samples indigenous people and others living in very remote regions of Australia. Moreover, HILDA also lacks coverage of those who are homeless, or incarcerated.

Future Research

The findings of this study open up several pathways for future research. Firstly, the specific measure of hardship used in this work has found common use in Australian social policy research over the past two-decades. However, it represents just one of many outcome-based approaches to assessing poverty. For example, the measure used in this study does not assess whether respondents were unable to pay for healthcare or essential medicines. Given this, future research should assess whether the associations observed within this work are robust to alternative measures of hardship.

Extending this further, the present study used a binary approach to classifying hardship – respondents were defined as experiencing hardship if they endorsed at least one of the seven scale items. While this approach maximises sensitivity – and has precedent in prior research (Butterworth et al., 2012; Kiely et al., 2015) – it obscures the specific form of hardship experienced. Therefore, future work should examine the degree to which associations vary according to specific items of hardship, such as food insecurity, or the inability to pay housing costs. Going a step further, future work should also attempt to identify common hardship profiles – with respect to specific co-occurring items of hardship – to assess their prevalence, their relationship with key sociodemographic factors, and their impact on health outcomes. This could also be conducted in concert with weighting items to reflect their severity. Moreover, it is possible that the nature of hardship may change over time. For example, Bray (2024) has highlighted the steady increase in the proportion of the Australian population citing internet access as 'essential' over the past two decades. Approaches to assessing financial hardship that ask respondents to categorise items as a necessity, and then use this information to determine which items continue to be included on a particular hardship scale, can help to account for such changing perceptions (Halleröd, 1994; Mack & Lansley, 1985). Finally, longitudinal analyses should trace the temporality in which hardships emerge, to pinpoint whether specific hardships arise first, whether certain hardships trigger others, whether there are consistent temporal patterns of hardship experience, and whether the risks associated with these different patterns varies.

Taking a longer horizon, future work should employ both life course and intergenerational approaches to examine how hardship experience during childhood shapes outcomes in later life. Research remains divided on whether socioeconomic advantages 'accumulate' throughout childhood – leading to substantial differences in achievement by early adulthood – or whether much of this apparent socioeconomic "Matthew Effect" can be accounted for by parental cognitive ability (Marks & O'Connell, 2021). Cohorts such as the Longitudinal Study of Australian Children (LSAC) now link childhood experiences to early adulthood, making it possible to examine the impact of early-life hardship and parental factors on outcomes in later life. Methods such as trajectory modelling and social sequence analysis could identify high-risk life-course profiles and determine the optimal timing for interventions. It would also be germane to examine factors associated with chronic hardship over the life-course that prevent families from escaping cycles of poverty across generations. Furthermore, mediation analyses are essential to identify risk and protective factors that alter the impact of hardship over the life course.

Finally, and as already noted earlier, prior research has shown that the relationship between financial hardship and mental health is highly contemporaneous (Butterworth et al., 2009; Butterworth et al., 2012; Kiely et al., 2015; Witteveen & Velthorst, 2020). Given this, future studies should collect finer-grained data – taking monthly or even weekly measures – to better detect rapid changes that occur following hardship experience, while providing greater insight into the nuanced temporal dynamics of this relationship.

Conclusion

Taken together, these results highlight that financial hardship poses a substantial public health risk, that it is sensitive to macro-economic shocks, and that it is especially concentrated amongst socioeconomically disadvantaged and psychologically vulnerable Australians. These findings highlight the significant public health implications of financial hardship, particularly the considerable association with poor mental health. This provides impetus for policy responses that directly target structural drivers of hardship as preventative health policy.

Chapter 4 – Assessing Temporality in the Bi-Directional Relationship Between Financial Hardship and Mental Health: A Random-Intercept Cross-Lagged Panel Analysis of HILDA Data

Abstract

Background: The previous chapter examined the prevalence of financial hardship – and it's two subdimensions, cashflow problems and deprivation – within Australia from 2001 to 2023, and assessed the strength of its relationship with mental health, and a broad array of key sociodemographic correlates. The previous chapter demonstrated three key findings: (1) Financial hardship consistently impacts a sizable minority of the Australian population; (2) Financial hardship is most prevalent amongst socioeconomically disadvantaged Australians; (3) Australians reporting poor mental health had the highest odds of experiencing financial hardship. The methodological approach of the previous chapter essentially comprised a large cross-sectional study that combined 23 waves of longitudinal HILDA survey data. Given all of this, there is a need to understand the striking relationship between financial hardship and mental health over time.

Aims: This chapter aimed to assess (1) whether within-person change in the experience of *financial hardship* is associated with a concurrent and/or lagged change in mental health over time; (2) whether within-person change in *mental health* is associated with a concurrent and/or lagged change in the experience of financial hardship over time, and; (3) the relative strength of the within-person and between-person components operating in this relationship.

Methods: The primary analysis for this study draws upon five waves (2019-2023) of the HILDA survey, comprising 16,082 unique individuals (47.0% male / 53.0% female) who contributed a total of 68,572 person-wave observations. Random-intercept cross-lagged panel modelling (RI-CLPM) was employed to examine the longitudinal bidirectional relationship between financial hardship and mental health, and to disentangle within-person dynamics from between-person 'trait' differences.

Results: Autoregressive terms for financial hardship experience (estimate = 0.117, SE = 0.012, $p < 0.001$) and mental health (estimate = 0.121, SE = 0.007, $p < 0.001$) demonstrated significant within-person stability over time. Within-wave deviations in financial hardship shared a significant, negative association with concurrent deviations in mental health

(estimates = -0.04 – -0.018, p's < 0.002). However, cross-lagged terms were not significant across all time periods. Specifically, higher financial hardship was associated with a very small but statistically significant improvement in mental health in the subsequent wave ($FH_{t-1} – MH_t$ = 0.017, SE = 0.007, p = 0.002); whereas mental health was not predictive of subsequent financial hardship ($MH_{t-1} – FH_t$ = -0.007, SE = 0.007, p = 0.333). The random-intercept terms showed that between-person effects accounted for a substantially greater share of variance than within-person effects in the relationship between financial hardship and mental health (RI-FH = 0.468, SE = 0.020, p < 0.001; RI-MH = 0.545, SE = 0.011, p < 0.001). Moreover, the negative covariance between the random-intercept terms (RI-FH, RI-MH = -0.217, SE = 0.010, p < 0.001), suggested that people who tend to experience greater levels of financial hardship, tend to also report lower trait mental health.

Conclusion: A consistent negative concurrent association was observed between financial hardship and mental health. However, cross-lagged associations between financial hardship and mental health were inconsistent, suggesting no clear evidence of lagged unidirectional or bidirectional effects. The evidence from this chapter suggests the relationship between financial hardship and mental health is primarily concurrent. Moreover, this chapter also highlighted that much of the observed relationship between financial hardship and mental health is attributable to stable, trait-level differences between individuals, rather than within-person variation over time. In other words, this relationship is largely driven by persistent structural differences between people, as opposed to momentary fluctuations in hardship experience or mental health. This suggests that the same people who tend to experience greater financial hardship, also tend to have poorer mental health. These findings have important implications for preventative intervention.

Introduction

Background

The previous two chapters of this thesis have provided substantial evidence highlighting the relationship between financial hardship and mental health. The systematic review provided a comprehensive synthesis of international evidence investigating this relationship, highlighting its strength and consistency. Building upon this, the previous chapter provided prevalence estimates of financial hardship within Australia from 2001 to 2023 and examined its relationship with key sociodemographic correlates and mental health over the same period. Again, a striking relationship between financial hardship and mental health was observed – Australians reporting very poor mental health had the highest odds of experiencing both cashflow problems and deprivation, two key indicators of financial hardship.

The majority of research included in the systematic review, however, examined this relationship using only two to three waves of data, and over a timespan of just three to four years. Furthermore, many studies did not disaggregate between and within-person effects. To this point, chapter three provided an essential foundation for more complex analyses – by characterising the experience of financial hardship across the Australian population. This approach maximised the available sample within the HILDA survey to provide precise population-average estimates of associations with key sociodemographic correlates between 2001 and 2023. However, it did not leverage the rich longitudinal structure of the data to explore within-person effects, or to examine the temporality and strength of both directional pathways comprising the relationship between financial hardship and mental health. In short, much of the prevailing literature, including the previous chapter, has provided thorough population-level assessments of which groups of people are most likely to experience the co-occurrence of financial hardship and poor mental health. However, relatively fewer studies have provided insight into the within-person temporal dynamics of this relationship, detailing what happens to an individual's mental health when they deviate from their usual level of financial hardship (and vice versa).

Given this, there is a need to apply more formal longitudinal methodology to understand how the relationship between financial hardship and mental health unfolds over time. The present chapter addresses this research gap by using random-intercept cross-lagged panel modelling to examine the temporal ordering between financial hardship and mental health, to present estimates of within-person effects for each directional pathway, and to quantify the relative strength of the within and between-person components operating in this relationship.

Social Causation and Health Selection

Assessing these bidirectional, within-person links is vital for gaining a deeper understanding of the processes through which financial hardship interacts with mental health over time. Whilst the strength of this association has been demonstrated repeatedly across varying contexts, evidence pertaining to its temporality and directionality remains unclear and inconclusive. This is perhaps unsurprising. The literature examining the bidirectional relationship between socioeconomic status and health more broadly, also reflects this ambiguity. Specifically, the extent to which poor socioeconomic conditions predispose people to poor health, and the extent to which a predisposition to poorer health is predictive of drifting into poorer socioeconomic positions remains an open question (Hudson, 2005; Perry, 1996; Warren, 2009). This inconclusiveness remains true for the focal relationship of this body of work, between financial hardship and mental health.

Two principal hypotheses have been proposed to explain each direction in the relationship between socioeconomic status and health – namely the *social causation* hypothesis and the *health selection* (or social drift/ social selection) hypothesis (Goldman, 1994). The social causation hypothesis posits that the experience of adverse socioeconomic conditions, such as poverty or financial hardship, raises one's risk of mental illness (Dohrenwend et al., 1992; Hudson, 2005; Kröger et al., 2015; Mossakowski, 2014). According to this hypothesis, socioeconomic disadvantage exposes individuals to conditions that lead to chronic stress arousal, such as poorer living conditions, material deprivation, precarious employment, more dangerous neighbourhoods, and lower social capital, which taken together, undermine psychological coping resources and heighten the risk of mental illness. In other words, the observed social gradient in health is a product of varying access to resources, support, and knowledge. In contrast, the health selection hypothesis posits that the experience of mental health problems may precipitate downward socioeconomic mobility, or inhibit an individual’s ability to rise beyond conditions of impoverishment. This outcome is deemed a consequence of the symptoms associated with poor mental health, leading to limited social functioning, increased health expenditure, impaired labour market participation or outright unemployment, and an inability to engage in or pursue higher education opportunities (Dohrenwend et al., 1992; Mossakowski, 2014; West, 1991). In other words, individuals who are in good health hold a greater capacity to achieve favourable positions in society, while poor health may hinder the pursuit of socioeconomic attainment.

Evidence in support of each hypothesis has been demonstrated in varying contexts, over several decades (Darin-Mattsson et al., 2018; Hoffmann et al., 2018; Jin et al., 2020; Kessler et al., 2008; Kröger et al., 2015; Marmot et al., 1991; Thomson et al., 2022, 2023; Warren, 2009; West, 1991). However, the relative strength of this evidence for each hypothesis is mixed. Broadly speaking, prevailing research has generally found the effect of changes in social position on mental health (social causation) to be larger than the effect of changes in mental health on social position (health selection) (Chandola et al., 2003; Marmot et al., 1991; Mossakowski, 2014). However, this trend is not universal.

For example, Chandola and colleagues (2003) conducted a cross-lagged panel model analysis using data from the Whitehall II study – a longitudinal study set up in 1985 that follows 10,308 civil servants in London. They found evidence of a small health selection effect amongst men, whereby poorer mental health was associated with a significant increase in subsequent financial deprivation. However, this health selection effect was more than two and a half times smaller than the corresponding social causation effect of greater financial deprivation leading to poorer subsequent mental health (Chandola et al., 2003). In line with this, Marmot and colleagues' (1991) cross-sectional analysis of Whitehall II data, demonstrated a very steep social gradient across a range of morbidity, mortality, and mental health outcomes by civil service (employment) grade – a pattern consistent with the social causation hypothesis. Specifically, British civil servants of lower status jobs reported significantly worse self-perceived health and symptoms of illness than those holding positions of higher status. Additionally, clear differences across job status were observed with respect to health-risk behaviours, such as rates of smoking, diet, and exercise. It is worth noting that Chandola and colleagues (2003) used cross-lagged panel models stratified by sex, that adjusted for prior health and civil service grade. This approach is designed to provide insight on temporal aspects of the SES – health relationship. On the other hand, Marmot and colleagues' (1991) findings were derived from cross-sectional analysis that adjusted for sex; an approach which precludes strong causal inference.

Similarly strong effects of social causation have been demonstrated by Wickham et al. (2017) – who demonstrated that transitions into poverty during early childhood were associated with an increased risk of subsequent mental health problems using data from the UK Millenium

Cohort Study – and Power and colleagues (2002) – who, using data from the 1958 British birth cohort, showed that gradients in psychological distress were downstream of the 'cumulative effect of multiple adversities experienced across the life-course'. Finally, Warren (2009) found very strong support for the social causation hypothesis operating between socioeconomic status and self-reported overall health, musculoskeletal health, and depression. Warren (2009) used structural equation modelling with data from the Wisconsin Longitudinal Study – a long-term survey of 10,317 men and women who were mostly born in 1939 and who graduated from Wisconsin high schools in 1957. Of note, as opposed to using a single variable for socioeconomic status, Warren derived a set of different latent factors from multiple variables to indicate socioeconomic status during childhood, in 1975, 1993, and 2004.

In contrast, Darin-Mattsson and colleagues (2018) found slightly greater support for health selection effects than social causation, when using path analysis to assess the relationship between financial hardship and psychological distress across the life-course in two longitudinal surveys from Sweden. More specifically, and with respect to social causation effects, they found that the experience of financial hardship in childhood was associated with greater psychological distress in adulthood. However, this effect appeared to taper off by old age, as there was no evidence to suggest that greater financial hardship was predictive of psychological distress between late adulthood and old age. Additionally, experiencing financial hardship in childhood was shown to increase the risk of having lower education and of not being employed – which, in turn increased the risk of psychological distress in later life. In other words, the link between childhood conditions and later-life health was mediated by education and employment. With respect to health selection, greater psychological distress was consistently predictive of greater financial hardship throughout all of adulthood.

Similarly, using random-intercept cross-lagged panel models, Cao et al. (2021) found a positive unidirectional effect whereby greater depressive symptoms led to increased financial stress throughout emerging adulthood. In contrast, longitudinal data from China provided evidence of social causation and health selection effects operating simultaneously in the relationship between poverty and depressive symptoms (Jin et al., 2020). Adding further nuance, Hoffmann et al. (2018) demonstrated that the relative importance of social causation and health selection effects changes across the life-course. This study used traditional cross-lagged panel models with data from the Survey of Health Aging and Retirement in Europe (SHARE) – a representative panel of people living in households across Europe. Their analysis was limited to respondents aged 50 or older, residing in Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Spain, Sweden and Switzerland. They divided the life-course into three periods – childhood (up to age 15), principal working age (between 30 and 49) and old age (50 to 90) and utilised different indicators of socioeconomic status to derive latent factors for socioeconomic status and health at each period. In short, they found that socioeconomic status and health shared only a weak relationship in childhood. From childhood to adulthood, they found evidence in equal measure to support small social causation and health selection effects. Finally, from adulthood to old age they found that social causation effects became stronger, while selection effects became trivial and no longer reached statistical significance. In short, the relative strength of social causation effects increased with age. However, an obvious limitation of this approach is that it required respondents to retrospectively recall events from their childhood. This strengthens the case for using long-term prospective data to confirm the strength of both directional pathways.

Additionally, studies have demonstrated variation according to the chosen analytic approach, the measure of socioeconomic status used, and the health outcome assessed (Dohrenwend et al., 1992; Huurre et al., 2005; Kröger et al., 2015). For example, Dohrenwend and colleagues (1992) demonstrated strong support for social causation effects in cases of depression, antisocial personality disorder, and substance abuse and dependence. However, in cases of schizophrenia they found greater support for health selection. Echoing this, a systematic review by Kröger et al. (2015), assessing the relative strength of social causation and health selection effects with respect to (predominantly) physical health, found empirical support for both hypotheses. However, their evidence did not support a preference for one directional pathway over the other. Moreover, the authors noted that this result may have been an artefact of the substantial heterogeneity in methodology characterising the included studies. In a similar systematic review and meta-analysis assessing how changes in income impact mental health amongst working-age adults, Thomson and colleagues (2022) also noted substantial methodological variation characterising included studies. Nonetheless, they concluded that changes in income 'probably' have an impact on mental health, particularly when the magnitude of the income change lifts an individual out of poverty. They also evidenced support for the deleterious impacts on mental health of income reductions. However, they expressed low certainty in these findings, given the included studies comprised small effect sizes and moderate to high risk of bias.

This lack of consensus possibly hints at the likelihood of both directions operating in concert via simultaneous or reciprocal pathways (Mossakowski, 2014). Indeed, Huurre and colleagues (2005) commented two decades ago, that given the understanding of health disparities at the time, gradients in health outcomes were unlikely to be explained by a single model. Given this, approaches capable of modelling both directional pathways are required, in order to accurately capture how deviations in each variable effect the other over time.

Within and Between-Person Effects

A key limitation of the prevailing literature is that many studies conflate stable, trait-level between-person differences, with temporary wave-to-wave state-level within-person fluctuations. Doing so risks interpreting otherwise stable between-person differences as within-person predictive associations. As noted by Warren (2009), 'researchers routinely recognise the complex interplay between SES and health across the life course, (however) they rarely utilize analytic techniques that allow them to model that complexity'. For example, it is possible that the same individuals who generally report experiencing greater financial hardship, also tend to have poorer mental health. In the absence of robust controls for such stable between-person differences, one runs the risk of observing this relationship as a spurious within-person cross-lagged association (Hamaker et al., 2015), such that greater financial hardship experience is predictive of poorer mental health. Accurately modelling both directional pathways operating between financial hardship and mental health necessitates disaggregating between *and* within-person levels of the longitudinal relationship.

To make the distinction clear, between-person effects refer to differences (across a sample) in people's average scores on a dependent variable as a function of their average scores on an independent variable – in other words, the difference between each individual's person-mean on a particular variable, as a function of differences in their person-mean on another. In contrast within-person effects refer to intraindividual change in a dependent variable, with respect to intraindividual change in a person's usual trait (mean) level on an independent variable – that is, how much each person's score on a particular variable deviates from their own overall person-mean on that variable over time. It then follows that a between-person association may be evident if people who, on average, experience greater levels of financial hardship, also tend to experience poorer mental health. On the other hand, a within-person association may be evident if, on occasions where an individual's experience of financial hardship is higher than their usual (mean) level, their mental health also drops below their usual (mean) level.

In turn, one can further expand on this disaggregation of between and within-person effects by applying it to each of the directional pathways expounded earlier. At the between-person level, the social causation direction posits that individuals who, on average, experience greater financial hardship will report a subsequent reduction in their mental health compared to individuals who experience less financial hardship. Conversely, the health selection direction posits that individuals who have poorer mental health will report greater financial hardship than individuals who experience better mental health. Put simply, the between-person level is comparing people who report different levels of financial hardship and mental health *to each other*. At the within-person level, the social causation direction posits that when an individual experiences greater financial hardship than their usual (mean) level, they will subsequently experience poorer mental health than their usual (mean) level. By comparison, the health selection direction posits that individuals who experience poorer mental health than their usual (mean) level, will subsequently experience greater financial hardship than their usual (mean) level. Importantly, the within-person level is comparing people *to themselves across time* (with respect to how their experience of financial hardship and mental health fluctuates).

Several recent studies have attempted to disaggregate the between- and within-person components of the bidirectional relationship between socioeconomic status and mental health. Again, results are mixed. O'Donnell and colleagues (2020) analysed data from the Building a New Life in Australia (BNLA) survey on resettled refugees and found evidence of within-person effects consistent with social causation and health selection, after controlling for between-person differences using random-intercept cross-lagged panel models (RI-CLPM). Using the same RI-CLPM approach that controlled for between-person differences, Yanez and colleagues (2024) also found evidence of modest within-person effects in both the social causation and health selection directions in an assessment of the relationship between financial hardship and depression amongst cancer patients. Similarly, Cao et al. (2021) also used RI-CLPM's to assess the bidirectional relationship between financial stress and depressive symptoms in a sample of emerging adults. They found evidence consistent with a within-person health selection effect, but no evidence in support of social causation. Notably, in all three of these studies, between-person effects were much stronger than the within-person effects (Cao et al., 2021; O'Donnell et al., 2020; Yanez et al., 2024). Moreover, studies by Prati (2024) and Su et al. (2021) – which used RI-CLPM to assess the bidirectional relationships between economic status and mental health, and income and mental health (respectively) – found evidence of strong between-person effects, but no evidence of within-person effects after controlling for between-person effects.

A Note on Causality

The social causation and health selection hypotheses represent *causal* theoretical models to describe and understand the association between socioeconomic status and health. Testing these respective directional pathways, as they pertain to the focal association of this thesis between financial hardship and mental health, within a formal causal framework is beyond the scope of this chapter. Nonetheless, disentangling the temporal ordering between financial hardship and mental health, and quantifying the strength of each directional pathway in this relationship represents a fundamental step towards demonstrating causality (Hill, 1965).

Aims

The aforementioned studies have examined within and between-person effects in the context of disentangling the relationship between socioeconomic status and mental health (Cao et al., 2021; O'Donnell et al., 2020; Prati, 2024; Su et al., 2021; Yanez et al., 2024). The broad aim of this chapter is to understand the longitudinal and bi-directional associations between financial hardship and mental health using nationally representative panel survey data from Australia, with a particular focus on their temporal ordering. More specifically, this chapter aims to assess (1) whether within-person change in the experience of financial hardship is associated with a concurrent and/or lagged change in mental health over time (consistent with the social causation hypothesis); (2) whether within-person change in mental health is associated with a concurrent and/or lagged change in the experience of financial hardship over time (consistent with the health selection hypothesis), and; (3) the relative strength of the within-person and between-person components operating in this relationship.

Methods

Data

The analysis for this study used data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. A detailed explanation of the HILDA survey can be found in the General Introduction (Chapter 1) under the section titled *Data Sources*.

Sample

The sample analysed in this study uses the five most recent waves (19-23; calendar years 2019-2023) HILDA survey. The HILDA Survey is a nationally representative household panel that has collected annual data on labour, family, income, and welfare dynamics since its inception in 2001 (Watson & Wooden, 2012). We removed all person-wave records that didn't comprise a completed Self-Completion Questionnaire (SCQ) and then retained all respondents who participated in wave 19 (2019). This yielded a total of 8,915 households and 16,082 individuals for the wave 19 (2019) sample. Table 11 provides the number of households and individuals comprising the analytic sample each year. In total, the 16,082 unique individuals (47.0% male / 53.0% female) contributed 68,572 person-wave observations over the five-wave period. In comparison, the wave 1 sample of the HILDA survey comprises 13,058 individuals (47.1% male / 52.9% female) from 7,245 households. Table 12 details the number and proportion of respondents providing data in 1-5 waves. The majority of respondents (67.4%) provided data in all five waves between 2019 and 2023.

Table 11

Analytic sample details

			Males		Females	
Year	**Households**	**N**	**n**	**%**	**n**	**%**
2019	8,915	16,082	7,552	47.0	8,530	53.0
2020	8,340	14,143	6,503	46.0	7,640	54.0
2021	8,201	13,373	6,139	45.9	7,234	54.1
2022	7,935	12,710	5,830	45.9	6,880	54.1
2023	7,788	12,264	5,607	45.7	6,657	54.3

Table 12
The number and proportion of respondents providing data in 1-5 waves

Waves Completed	n	%
5	10,834	67.4
4	1,902	11.8
3	1,208	7.5
2	1,032	6.4
1	1,106	6.9

Measures

This analysis in this study used measures of *sex* and *age*, *time block*, *financial hardship*, and *mental health*. Details pertaining to how each of these items have been assessed and defined can be found in the General Introduction (Chapter 1) under the section titled *Data Sources*.

Analysis

Statistical analyses were conducted using R version 4.5.0 (R Core Team, 2025). At each wave, correlation coefficients were calculated to assess the relationship between financial hardship and mental health. Given both variables were scored continuously, correlations were estimated using Pearson's r.

A random-intercept cross-lagged panel model (RI-CLPM) was employed to examine the longitudinal relationship between financial hardship and mental health, and to disentangle within-person dynamics from between-person 'trait' differences. RI-CLPM's analyse the degree of stability within a given set of constructs over time, along with whether cross-lagged relationships exist between these same constructs over time. Compared to the traditional cross-lagged panel model (CLPM) approach, a RI-CLPM utilises a random-intercept term to account for trait-level, between-person differences (Hamaker et al., 2015). In turn, the autoregressive and cross-lagged terms are intended to exclusively reflect the within-person variation contained in the focal outcome of interest. The RI-CLPM approach typically provides a better fit to the data than using a traditional CLPM (Lucas, 2023; Mulder & Hamaker, 2021).

A model comprising five lags (2019-2023) was fitted using the *lavaan* package (v0.6-19) (Rosseel, 2012). Given the varying scales with which our focal measures were scored (financial hardship, 0-7; SF-36 mental health, 0-100) both outcomes were z-standardised prior to model estimation. Model parameters were estimated using Full-Information Maximum Likelihood (FIML) to handle missing data, and the robust maximum likelihood (MLR) estimator. FIML uses all data, including partially-complete cases, and is designed to be unbiased under missing-at-random assumptions (Enders, 2022). Given this, participants with at least one wave of data were included in model estimation. Of the sample assessed, five records were empty on each of the key outcomes at all waves and automatically removed, leaving a total sample of 16,078 respondents at baseline in 2019 (wave 19). A table comparing respondents who completed all waves versus those missing at least one wave of data, across sex, age, financial hardship and mental health, is provided in Appendix C.5. The prevalence of financial hardship was lower amongst respondents who completed all waves, compared to those missing at least one wave (17.7% vs. 23.6%). Similarly, average SF-36 mental health scores were higher amongst respondents present in all waves ($M = 72.0$, $SD = 17.9$) compared to those missing at least one wave ($M = 68.9$, $SD = 19.0$). Model fit was evaluated using the following fit indices: Robust Comparative Fit Index (CFI), Robust Tucker-Lewis Index (TLI), root mean square error of approximation (RMSEA) with 90% CI, standardized root mean square residual (SRMR). CFI and TLI values ≥ 0.95, RMSEA values ≤ 0.06, and SRMR values ≤ 0.08 are benchmarks that indicate good model fit (Hu & Bentler, 1999; Mackinnon et al., 2020). Standardised estimates, standard errors, and p-values with an alpha of 0.05 were reported for all models. A glossary describing model parameters and guidance for interpretation is provided below in Table 13.

Table 13
Glossary of model parameters and interpretation

Parameter	Model Term(s)	Description	How to Interpret
Random-intercept variance	Var(RI-FH) Var(RI-MH)	This provides an estimate of the stable (trait-level) variability in average FH and MH (between-person).	Larger values indicate greater between-person heterogeneity in trait FH/MH.
Random-intercept covariance	Cov(RI-FH, RI-MH)	This represents the association between an individual's typical (person-mean) FH and MH scores (between-person).	For example, negative values indicate that higher average FH is associated with lower average MH.
Autoregressive	$FH_{t-1} \rightarrow FH_t$ (a1) $MH_{t-1} \rightarrow MH_t$ (a5)	This represents the degree of within-person stability in financial hardship/mental health scores over time (net of RI and CL terms).	A 1 standard deviation (SD) higher-than-usual score in FH/MH at wave t−1 predicts a β SD change in FH/MH at wave t.
Cross-lagged	$FH_{t-1} \rightarrow MH_t$ (b5) $MH_{t-1} \rightarrow FH_t$ (b1)	This represents the cross-lagged association between FH/MH (t-1) and MH/FH (t) (within-person) (net of RI and AR terms).	A 1 standard deviation (SD) higher-than-usual score in FH/MH at wave t−1 predicts a β SD change in MH/FH at wave t.
Residual covariance	Cov(FH_t - MH_t) (e1–e5)	This provides the concurrent association between (within-person) deviations in FH and MH (net of RI, AR, and CL terms).	For example, negative values indicate that when FH is above average at wave t, MH tends to be lower than average at wave t (and vice versa).
Residual variance	Var(FH_t) Var(MH_t)	This provides the unexplained within-person variability by wave (net of RI, AR, and CL terms).	Larger values indicate more unexplained within-person variability.

* AR = Autoregressive; CL = Cross-Lagged; RI = Random-Intercept.

** Variables were z-standardised. β coefficients are reported in SD units; variances are reported in SD^2.

*** FH = Financial Hardship; MH = Mental Health

Stationarity refers to when paths are time-invariant and assumes that the underlying process is consistent regardless of when measurements are taken. To assess the appropriateness of stationarity constraints three models were compared:

1. *Unconstrained* – A model without any stationarity constraints.
2. *Fully Constrained* – A model with full stationarity constraints imposed on autoregressive, cross-lagged, and residual covariance terms.
3. *Part Constrained* – A model with stationarity imposed on autoregressive and cross-lagged terms, but freely estimated residual covariance terms.

All three candidate models demonstrated excellent absolute fit (CFI = 0.995, TLI ~ 0.995; RMSEA = 0.025-0.03; SRMR = .022) (Table 14). Model comparison was undertaken using robust Satorra-Bentler χ^2 difference tests, and comparison of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Compared to the unconstrained model, the more parsimonious fully constrained model did not demonstrate a significant decrement in model fit ($\Delta\chi^2 = 21.92$, $p > 0.05$), supporting the decision to impose stationarity constraints. However, freeing the residual covariance terms between financial hardship and mental health across waves slightly reduced AIC (316,956 vs. 316,976) and led to a statistically significant improvement in model fit over the fully constrained model ($\Delta\chi^2 = 16.09$, $p < 0.001$). Given this, the partially constrained model was retained as the final model. Complete model fit comparison statistics (Satorra-Bentler χ^2 difference test) are detailed in Appendix C.1. Full model outputs for both the unconstrained and fully constrained models are detailed in Appendix C.2.

A series of sensitivity analyses were conducted to test the robustness of the main findings. First, the same partially constrained model structure was assessed using binary measures of financial hardship (0 = no hardship, 1 = hardship) and mental health (0 = poor mental health, 1 = good mental health; clinical cutoff score = 60 (Kelly et al., 2008)). Second, the model structure was evaluated across the three preceding time periods – 2001-2006, 2007-2012, and 2013-2018 – to determine consistency in the relationship between financial hardship and mental health over time. Third, a within-between mixed-effects (Mundlak) model (with person-level random intercepts) was performed over the 2019-2023 time-period to ascertain robustness of the primary RI-CLPM. This approach decomposes the variance in a repeatedly assessed predictor into the amount by which each person deviates from the overall grand mean of all persons, and the amount by which each observation from each person deviates from their own, person-centred mean (Twisk & De Vente, 2019). In so doing, this yields both the between-person and within-person variance (respectively), upon which a given outcome can be regressed over (Bell et al., 2019; Howard, 2015).

Table 14
Model fit indices for candidate models

Model	Model χ^2 (scaled)	df	CFI (robust)	TLI (robust)	RMSEA (robust)	90% CI RMSEA	SRMR
1. Unconstrained	233.79	31	0.995	0.993	0.03	0.026 – 0.034	0.022
2. Fully Constrained	241.28	47	0.995	0.995	0.025	0.022 – 0.028	0.022
3. Part Constrained	224.91	43	0.995	0.995	0.025	0.022 – 0.029	0.022

Results

Correlations between Financial Hardship Experience and Mental Health

Table 15 presents Pearson correlation coefficients between financial hardship experience and mental health at each wave. Financial hardship experience was positively associated with financial hardship experience at all subsequent waves (*r* range, 0.487 to 0.605). The correlation between financial hardship weakened as the time spanning assessment periods increased. Mental health was also positively correlated with mental health at all waves (*r* range, 0.599 to 0.715). Like financial hardship, the correlations between mental health weakened as the time between assessment periods increased. Financial hardship experience and mental health were negatively correlated at all time points, indicating that higher financial hardship is associated with lower mental health (*r* range, -0.289 to -0.224). Additionally, the correlations between financial hardship and mental health were strongest when each was measured at the same time point, and weakened as the time between the assessment of each increased – providing evidence for some measure of temporality between these two factors.

Table 15
Pearson correlation coefficients between financial hardship and mental health (SF-36) from wave 19 to 23 (2019-2023) of the HILDA Survey

	Financial Hardship					Mental Health				
	W 19	**W 20**	**W 21**	**W 22**	**W 23**	**W 19**	**W 20**	**W 21**	**W 22**	**W 23**
Financial Hardship										
W 19	1									
W 20	0.588	1								
W 21	0.527	0.575	1							
W 22	0.543	0.525	0.593	1						
W 23	0.510	0.487	0.547	0.605	1					
Mental Health										
W 19	-0.278	-0.258	-0.242	-0.254	-0.256	1				
W 20	-0.234	-0.260	-0.244	-0.249	-0.245	0.675	1			
W 21	-0.234	-0.240	-0.264	-0.254	-0.254	0.635	0.704	1		
W 22	-0.246	-0.247	-0.243	-0.285	-0.270	0.639	0.660	0.710	1	
W 23	-0.224	-0.227	-0.237	-0.247	-0.289	0.599	0.630	0.667	0.715	1

Random-Intercept Cross-Lagged Panel Models

Table 16 and Figure 8 provide detail of all parameter estimates contained within the partially constrained model. Both random-intercept terms suggest substantial between-person variance in both financial hardship Var(RI-FH) = 0.468 (SE = 0.020, $p < 0.001$) and mental health Var(RI-MH) = 0.545 (SE = 0.011, $p < 0.001$). Moreover, the covariance between the two random-intercepts was negative, Cov(RI-FH, RI-MH) = -0.217 (SE = 0.010, $p < 0.001$), indicating that people who experience greater trait financial hardship, tend to report lower trait mental health. All autoregressive paths (a1, a5) were significant and positive, indicating that both financial hardship and mental health were highly stable over time (a1 = 0.117, SE = 0.012, $p < 0.001$; a5 = 0.121, SE = 0.007, $p < 0.001$). Within the cross-lagged effects, higher financial hardship at one wave was associated with a very small but statistically significant improvement in mental health in the subsequent wave b5 (FH_{t-1} – MH_t) = 0.017, (SE = 0.007, $p = 0.002$). However, the reverse cross-lagged path assessing whether mental health was predictive of financial hardship at subsequent waves was not significant, b1 (MH_{t-1} – $FH_{t)}$ = -0.007 (SE = 0.007, $p = 0.333$). The covariances between financial hardship and mental health at each wave were small but negative and significant (e1-e5 = -0.04 – -0.018, p’s < 0.002) suggesting that within-wave deviations in financial hardship were associated with concurrent deviations in mental health.

Table 16

Standardised parameter estimates for the partially constrained random-intercept cross-lagged panel model

		Partially Constrained RI-CLPM – 2019-2023			
Outcome	**Predictor**	**Parameter**	**Estimate (β)**	**SE**	**p-value**
Autoregressive Terms					
FH_t	FH_{t-1}	a1	0.117	0.012	**<0.001**
MH_t	MH_{t-1}	a5	0.121	0.007	**<0.001**
Cross-lagged Terms					
FH_t	MH_{t-1}	b1	-0.007	0.007	0.333
MH_t	FH_{t-1}	b5	0.017	0.006	**0.002**
Covariance Terms					
FH - W19	SF-36 MH - W19	e1	-0.040	0.007	**<0.001**
FH - W20	SF-36 MH - W20	e2	-0.018	0.006	**0.002**
FH - W21	SF-36 MH - W21	e3	-0.020	0.005	**<0.001**
FH - W22	SF-36 MH - W22	e4	-0.025	0.006	**<0.001**
FH - W23	SF-36 MH - W23	e5	-0.044	0.006	**<0.001**
RI - FH	RI - MH		-0.217	0.010	**<0.001**
Variance Terms					
RI - FH	RI - FH		0.468	0.020	**<0.001**
RI - MH	RI - MH		0.545	0.011	**<0.001**
FH - W19	FH - W19		0.491	0.017	**<0.001**
FH - W20	FH - W20		0.472	0.018	**<0.001**
FH - W21	FH - W21		0.452	0.018	**<0.001**
FH - W22	FH - W22		0.431	0.017	**<0.001**
FH - W23	FH - W23		0.454	0.018	**<0.001**
SF-36 MH - W19	SF-36 MH - W19		0.418	0.009	**<0.001**
SF-36 MH - W20	SF-36 MH - W20		0.345	0.007	**<0.001**
SF-36 MH - W21	SF-36 MH - W21		0.321	0.007	**<0.001**
SF-36 MH - W22	SF-36 MH - W22		0.315	0.007	**<0.001**
SF-36 MH - W23	SF-36 MH - W23		0.348	0.008	**<0.001**

* Autoregressive (a1, a5) and cross-lagged (b1, b5) paths were constrained to be equal across adjacent waves (19-23).

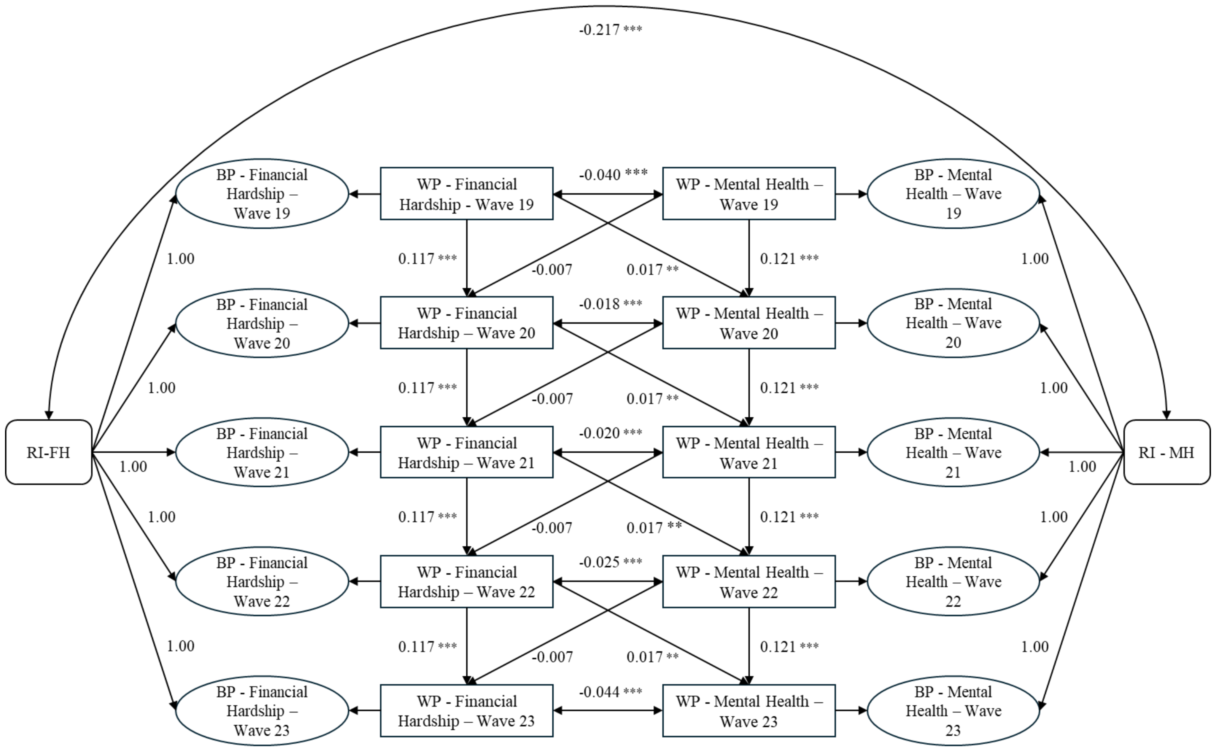

Figure 8

RI-CLPM – Relationship between financial hardship and mental health – waves 19-23

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

** BP refers to between-person variance; WP refers to within-person variance. Pathways from random intercepts (RI-FH and RI-MH) to between-person terms constrained to 1.00 to isolate between-person factor.

Sensitivity Analyses

Binary Financial Hardship / Mental Health Measures

The first sensitivity analysis comprising binary measures of financial hardship and mental health confirmed the findings detailed in the primary (partially constrained) model (Table 16). Model fit statistics and all parameter estimates for this sensitivity analysis can be found in Appendix C.3.

2001-2006, 2007-2012, 2013-2018 Models

Model fit indices and standardised parameter estimates for the 2001-2006, 2007-2012, 2013-2018 RI-CLPM's can be found in Appendix C.4. Consistent with the primary analysis, the random-intercept terms in all preceding time periods suggested substantial between-person variance in financial hardship Var(RI-FH) = 0.441 – 0.533 ($p < 0.001$) and mental health Var(RI-MH) = 0.451 – 0.519 ($p < 0.001$). Moreover, the significant inverse relationship observed between the financial hardship and mental health random-intercept covariance term was also preserved over all three prior time periods Cov(RI-FH, RI-MH) = -0.171 – -.204 ($p < 0.001$). Consistent with the primary analysis, all autoregressive paths (a1, a5) were significant and positive (a1 = 0.129 – 0.185, $p < 0.001$; a5 = 0.108 – 0.141, $p < 0.001$). In the primary RI-CLPM, spanning 2019-2023, prior financial hardship was associated with a very small, but significant improvement in subsequent wave mental health. However, this result was not replicated in models assessing the preceding three time-periods, suggesting the observed association in 2019-2023 may have been anomalous. In contrast, prior mental health was associated with a small, yet significant reduction in subsequent financial hardship (b1 = -0.015 – -.0.025, $p < 0.001$) in 2001-2006 and 2007-2012. Akin to the primary analysis, the within-wave financial hardship-mental health covariance terms (e1-e5) for all three preceding time periods were negative and statistically significant, ranging from -0.02 to -0.07 ($p < 0.001$).

Within-Between Mixed-Effects (Mundlak) Model

Counter-intuitively, the cross-lagged terms in the primary analysis – spanning 2019-2023 – demonstrated that higher financial hardship experience predicted a very small, but significant increase in subsequent wave mental health. Although this result was not replicated in the subsequent models it demanded further investigation, using an alternative but complementary analytic approach, to determine whether it reflected true causality, or was an artefact of model specification (Lucas, 2023; Sorjonen et al). Table 17 details the overall correlations between concurrent and lagged within-person deviations in financial hardship and within-person deviations in mental health. Correlations indicate that increases above an individual's average financial hardship were associated with a slight reduction in concurrent average mental health (*r* = -.075). Prior financial hardship (i.e., lagged financial hardship) shared a very weak, but still positive correlation with subsequent mental health (*r* = .017).

Table 17
Overall correlations between concurrent and lagged within-person deviations in financial hardship and within-person deviations in mental health

	Financial Hardship	Mental Health	Financial Hardship (Lagged)	Mental Health (Lagged)
Financial Hardship	1.000			
Mental Health	-0.075	1.000		
Financial Hardship (Lagged)	-0.198	0.017	1.000	
Mental Health (Lagged)	-0.002	-0.185	-0.067	1.000

Table 18 details the results of the within-between mixed effects regression model with random-intercepts, estimating the strength of the association between concurrent and lagged within-person deviations in financial hardship, between-person mean levels of financial hardship, and lagged SF-36 mental health scores with current SF-36 mental health scores. This model demonstrated significant associations between both within-person deviations in financial hardship and average financial hardship (between-person) with mental health scores. Specifically, a one unit increase in average financial hardship was associated with a 6.5 point lower score on the SF-36 mental health scale ($\beta = -6.50$, $p < 0.001$). Moreover, a one unit increase above an individual's average financial hardship, was associated with a 1.2 unit decrease in subsequent mental health ($\beta = -1.20$, $p < 0.001$). Finally, a one unit increase above an individual's average mental health in a prior wave, was associated with a -0.15 decrease in subsequent mental health ($\beta = -0.15$, $p < 0.001$).

Taken together, this highlights that the stable between-person trait effect of financial hardship ($\beta \sim -6.50$) is approximately five times greater than the within-person state effect ($\beta \sim -1.20$). In other words, an individual's overall mean level of financial hardship experience was more strongly associated with changes in mental health than the fluctuations in hardship they may have experienced from wave-to-wave.

Table 18

Multivariable mixed effects regression model with random-intercepts, estimating the within- and between-person association between financial hardship experience and mental health

* Bold denotes statistical significance

Characteristic	Beta	95% CI	p-value
Between or Within			
Mean Financial Hardship (Between)	-6.50	-6.70, -6.20	**< 0.001**
Mental Health Dev. (Within) - Lagged	-0.15	-0.16, -0.14	**< 0.001**
Financial Hardship Dev. (Within)	-1.20	-1.30, -1.00	**< 0.001**
Financial Hardship Dev. (Within) - Lagged	-0.07	-0.23, 0.08	0.4

Abbreviation: CI = Confidence Interval

Note: Mixed model with random-intercepts for person

Discussion

General Findings

A compelling body of evidence has consistently demonstrated a substantial association between the experience of financial hardship and mental health. However, the temporal ordering between these constructs, and the relative strength of each directional pathway within this reciprocal relationship remains less clear. Specifically, the extent to which the experience of financial hardship leads to poor mental health, and the extent to which poor mental health contributes to the experience of financial hardship is not fully understood. Employing a RI-CLPM, that disaggregated the between and within-person effects operating in the association between financial hardship and mental health, enabled a test of how changes in financial hardship, and changes in mental health are linked within individuals, while controlling for stable between-person effects.

Given this, the first aim of this chapter was to examine whether within-person change in the experience of financial hardship was associated with concurrent and/or lagged changes in mental health over time, and vice versa. Secondly, this chapter also aimed to quantify the relative strength of the within and between-person associations in this relationship. The primary analysis spanned from 2019 to 2023. However, a series of sensitivity analyses were also conducted that spanned 2001-2006, 2007-2012, and 2013-2019. Taken together, these analyses revealed several trends.

Firstly, the auto-regressive terms demonstrated significant stability in the experience of financial hardship and reported mental health over time, in all assessed time-periods. In other words, an individual's prior mental health was significantly predictive of their mental health in follow-up waves. Similarly, their level of financial hardship experience was significantly predictive of their experience of financial hardship in follow-up waves.

With respect to the principal aims of this study, analyses of covariance terms across all four time periods demonstrated a significant and negative association between concurrent financial hardship experience and mental health, indicating that a within-person increase in financial hardship was associated with a concurrent reduction in mental health (and vice versa).

However, this relationship did not remain significant across all time periods when assessing the cross-lagged terms. Specifically, prior financial hardship was only associated with subsequent mental health in the 2019-2023 time period. Conversely, prior mental health demonstrated a small negative association with subsequent financial hardship experience in the 2001-2006 and 2007-2012 time periods – however, this association was not observed in 2013-2018 and 2019-2023.

With respect to the second aim of this study, the random-intercept terms highlighted that a far greater share of the variance in financial hardship and mental health scores is attributable to stable, trait-level differences between individuals, than wave on wave within-person fluctuations. In other words, the differences *between* people in terms of financial hardship experience and mental health were substantially greater than the wave-to-wave fluctuations in financial hardship and mental health individuals experienced within themselves over time. Moreover, in all time periods the covariance between the random-intercepts for financial hardship and mental health was negative and significant, indicating that individuals with greater trait-levels of financial hardship were more likely to report lower trait mental health, and vice versa.

Interpretation

The most salient finding from this analysis was the strength and consistency of the between-person effect. This suggests that people who tend to experience greater financial hardship, also tend to have poorer mental health. However, this finding is not unique. A range of recent studies that have assessed the relationship between income, and various conceptions of financial hardship, with mental health using the same RI-CLPM approach have consistently demonstrated substantially larger between-person effects than within-person effects (Cao et al., 2021; O'Donnell et al., 2020; Prati, 2024; Su et al., 2021; Yanez et al., 2024). Nonetheless, this finding has significant implications. Firstly, it may hint at an underlying factor (or indeed factors) linking the co-occurrence of greater hardship and poorer mental health. Given that stable between-person differences appear to have a far greater effect than short-term within-person fluctuations in hardship experience and mental health, short-term interventions designed to alleviate financial hardship or enhance mental health may lack the ability to effect substantial and enduring improvement amongst a subset of the population for whom socioeconomic disadvantage is entrenched across multiple domains, or amongst those enduring sustained and serious mental health problems.

The finding that concurrent financial hardship and mental health shared a consistent negative relationship aligns with prior work that has evidenced the immediacy of this relationship

(Butterworth et al., 2009; Butterworth et al., 2012; Kiely et al., 2015; Witteveen & Velthorst, 2020). Whilst this analysis did not disentangle the directionality of the concurrent relationship, it suggests that experiencing greater financial hardship negatively impacts mental health relatively immediately, and/or periods of poor mental health very quickly lead to greater financial hardship. This is likely due, in the first case, to financial hardship precipitating an immediate increase in stress, anxiety or feelings of helplessness (social causation), and in the second case, to poor mental health leading to spells out of the labour market or incurring increased out of pocket medical expenses (health selection). A third possibility, is that financial hardship and poorer mental health tend to co-occur in response to adverse life events.

Relatively small effects consistent with health selection were evident operating in the mental health to financial hardship directional pathway throughout the 2001-2006 and 2007-2012 time periods. This is consistent with a range of prior work that has also found evidence of poorer mental health leading to greater socioeconomic disadvantage or increased financial hardship (Cao et al., 2021; Chandola et al., 2003; Darin-Mattsson et al., 2018; Jin et al., 2020).

The finding that greater financial hardship was associated with a very small but statistically significant improvement in subsequent mental health between 2019 and 2023 was counter intuitive. This result prompted further investigation by way of replicating the 2019-2023 RI-CLPM across earlier time periods, and conducting a within-between mixed-effects (Mundlak) model. In short, the counter-intuitive finding from the 2019-2023 period was not replicated in any of the models assessing the three earlier periods, or in the within-between mixed-effects model. This raises two possibilities. Firstly, this result may have been an artefact of model specification. Recent methodological research has highlighted that fitting a RI-CLPM without modelling within-wave directional effects can result in spurious or biased cross-lags, or even effects in the opposite direction of the true effect. This is particularly evident when the focal variables refer to different reference timeframes, as applies to this study where financial hardship was assessed over the previous 12 months, while mental health was assessed over the preceding four weeks (Lucas, 2023; Muthén & Asparouhov, 2024, 2024; Sorjonen et al., 2023). (This is discussed further below in the section covering strengths and limitations.)

Strengths and Limitations

As noted in the previous chapter, a primary strength of this analysis is the use of very high quality longitudinal panel data from the HILDA survey. Firstly, the longitudinal structure of the HILDA survey allows for the investigation of how relationships between variables unfold over time. Furthermore, it also enables one to disaggregate the between and within-person components of the relationship under investigation, and to quantify their relative contribution. Additionally, re-interview rates in the HILDA survey have commonly exceeded 93 percent. This means that a sizeable majority of panel members have been observed consistently, and provided repeated measures over multiple time-points. Importantly, this enables robust findings to be derived from longitudinal analyses, and reduces bias attributable to sample attrition, particularly where members who drop out are systematically different to those who remain.

The use of RI-CLPM is another key strength of this work. This approach extended upon the static pooled analysis conducted in the previous chapter, which provided population-averaged effects over 23 waves, by providing insight into how the relationship between financial hardship and mental health unfolds over time. Moreover, the use of RI-CLPM's overcomes a significant limitation of the traditional CLPM. Specifically, CLPM's conflate stable, between-person associations with transient within-person fluctuations. This can lead to spurious cross-lagged effects (Lucas, 2023). The RI-CLPM overcomes this by including a pair of random-intercepts in the model structure. Together, the random-intercepts account for the stable, time-invariant between-person component of the modelled relationship, disaggregating it from the within-person component. In turn, this allows the cross-lagged paths to be interpreted as clean within-person deviations from an individual's usual (mean) level (Hamaker et al., 2015). As described by Lucas (2023), in a CLPM the cross-lagged paths reflect an association between two variables, whereas in a RI-CLPM the cross-lags reflect "associations among wave-specific deviations from a person's stable trait level".

Nonetheless, some important limitations to this study should also be acknowledged. Firstly, a model containing all available waves of HILDA Survey data, from 2001 to 2023 was not reported in this chapter. Modelling 23 waves of data using a RI-CLPM led to challenges with model convergence. Given this, a model comprising a shorter time period, that produced stable and interpretable estimates was preferred. Secondly, as per the preceding chapter, models comprising the subdomains of financial hardship (namely *cashflow problems* and *deprivation*) were not assessed. The aim of this chapter was to understand the overall bidirectional relationship between financial hardship and mental health, and in doing so, lay the groundwork for more fine-grained analyses. Future work should examine whether the bidirectional relationship between financial hardship and mental health differs when disaggregated by hardship sub-domain. Thirdly, whilst financial hardship and mental health were assessed at the same time point, they each refer to different reference timeframes. Specifically, financial hardship is measured over the preceding twelve months, however mental health is measured over the preceding four weeks. Prior research has argued that when this situation arises between two variables of interest in longitudinal panel data, it is possible to infer 'within-wave directionality' (Speyer et al., 2025). In other words, whilst the data has been collected at the same time, the varying reference timeframes of the focal measures actually reflect a (within-wave) temporal sequence. Specifically, the within-wave temporal ordering may be assumed to run from the variable with the longer reference timeframe predicting the variable with the shorter reference timeframe. With respect to the analysis in this chapter, one could assume that financial hardship (assessed over the past twelve months) predicts the mental health outcome (assessed over the past four weeks) within the same wave. Currently, it is common for concurrent associations in a RI-CLPM to be modelled as residual covariances. However, Speyer et al., (2025) argues that this may bias cross-lagged effects, while also losing insight on potential within-wave temporal effects. Instead, they propose extending the current RI-CLPM, by specifically modelling the concurrent associations as within-wave directional pathways. The analysis presented within this chapter did not model these.

Related to this, the varying reference timeframes of the focal variables invites the possibility of temporal misalignment, which undermines the key aim of estimating directional pathways. Specifically, in the social causation directional pathway, the *exposure* of financial hardship (past 12 months) may have occurred months before the *outcome* of poor mental health (assessed over the past 4 weeks). In other words, given the annual structure of the HILDA survey, (1) individuals who experienced financial hardship at the start of the twelve month interval may have experienced relatively immediate reductions to their mental health that were not recorded; or (2) if reductions to mental health were recorded in the four weeks preceding data collection, they may not be temporally associated with a recorded experience of financial hardship that occurred many months prior. Similarly, in the health selection directional pathway, the *exposure* of poor mental health (past 4 weeks) may have come after the *outcome* of financial hardship (past 12 months). Together, the impact of this would be to diminish the effect sizes of observed associations. More generally, the twelve-month interval between waves may be too long to capture the precise temporal relationship between these variables. In other words, this may be masking effects that occur over a much shorter time period. Prior research has indeed shown the relationship between financial hardship and mental health to be relatively immediate (Butterworth et al., 2009; Butterworth et al., 2012; Kiely et al., 2015; Witteveen & Velthorst, 2020). Given this, data collected over a much finer grained time period may be needed to fully understand this relationship. Additionally, this also signals a need for the focal variables to be assessed over consistent time frames.

Additionally, the assessed models did not include time-varying confounders. Again, this may lead to bias in cross-lagged estimates. However, this decision was made for two key reasons. Including time-varying confounders would have substantially increased model complexity, and potentially introduced problems with convergence. Secondly, many of the potential candidate time-varying confounders (such as employment status, education, area-level disadvantage, or income) are likely to be both cause and consequence (i.e., endogenous) of the focal study variables. In such instances, inclusion without a carefully considered causal rationale may elicit misleading estimates (Mund et al., 2021). Given these two reasons, inclusion of time-varying confounders was deemed beyond the scope of this study.

Similarly, the analysis comprised a single RI-CLPM that provided averaged estimates over all respondents. This approach may have hidden substantive effects occurring amongst sub-groups of the sample. Given this, future research should explore whether estimates vary according to key socio-demographic factors such as age, birth-cohort, gender, education, area-level disadvantage, and income or wealth.

Finally, it should be noted that that the primary analysis of this chapter (from 2019-2023) covered the period where COVID-19 occurred. Within Australia, this was a period punctuated by enduring orders to stay at home (or 'lockdowns'), restrictions on the ability to travel and move around, widespread economic disruption, government mandates, changes to the provision of social welfare benefits, and inflationary shocks to the Australian economy. In the previous chapter, a notable rise in the prevalence of financial hardship was observed during this period. Similarly, it is arguable that population mental health was also impacted owing to these unique circumstances. Together, it is possible that these external period effects may have affected cross-lagged estimates.

Future Research

The findings presented in this chapter provide opportunities for a range of future research. Firstly, and as alluded to above, several refinements to the model presented in this work would provide answers to more specific research questions. Firstly, the addition of time-varying confounders would provide insight into how the relationship between financial hardship and mental health changes with the inclusion of key sociodemographic controls. Similarly, RI-CLPM analyses that are grouped according to key socio-demographic factors would identify whether there exists variation in cross-lagged estimates with respect to age, birth cohort, gender, education, area-level disadvantage, and income or wealth. For example, the prior chapter, along with numerous related contemporary studies, identified a startling increase in the prevalence of poor mental health amongst teenagers and young adolescents, particularly females (Davidson et al., 2023; Eurostat, 2025; Rahman, 2019; Tran et al., 2025). Recent research has also identified that the mental health of more disadvantaged members of society has declined, whereas that of more affluent individuals has remained constant (Goldman et al., 2018). Thus, it would be germane to assess the degree to which varying social causation and health selection effects may be operating across these specific sociodemographic groups.

Future research should also attempt to assess the relationship between financial hardship and mental health with measures using consistent timeframes, and longitudinal data with a significantly shorter interval than twelve months. It is possible that this length of time is too long to observe cross-lagged effects, and to therefore gain a precise understanding of temporal ordering. Furthermore, the modelling of additional within-wave directional pathways operating ‘concurrently’ may assist in providing insight into the contemporaneousness of this relationship, while improving the accuracy of cross-lagged effects estimated over longer time periods (Speyer et al., 2025).

The most prominent finding from this work was the between-person component of the financial hardship - mental health relationship was much larger than the within-person effect. This finding should be explored further. For example, life-course approaches that explicitly model these between-person differences may help to identify sociodemographic correlates that account for this variation. It is also possible that there may be an underlying factor, or factors, such as education, employment status, personality characteristics, or intergenerational influences driving this relationship. In a study using latent transition analysis, Sacker et al., (2013) highlighted how non-employment *mediated* the health selection effect operating from health to poverty, and *confounded* the social causation effect operating from poverty to health. In other words, poor health led to increased non-employment and a greater risk of experiencing poverty. Additionally, the pathway from poverty to poor health may actually be an artefact of non-employment being strongly related to both poverty and poor subsequent health.

Finally, the social causation and health selection hypotheses are causal models designed to describe the relationship between socioeconomic status and health, including the observed disparities in health outcomes that commonly follow a distinct inverse social gradient. Future work should seek to assess these hypotheses in a formal causal framework.

Conclusion

This chapter provides evidence of a consistent negative, concurrent *within-person* association between financial hardship and mental health. This finding suggests that when individuals experience greater financial hardship than they usually do, they also experience poorer (than usual) mental health (and vice-versa). Given the way in which the RI-CLPM was structured, the bidirectionality of this concurrent effect was not disentangled. However, new approaches to random-intercept cross-lagged modelling comprising directional 'within-wave' pathways have made this possible (Speyer et al., 2025), opening up opportunities for novel research.

The assessed cross-lagged associations were inconsistent and provided no clear evidence of unidirectional or bidirectional social causation or health selection effects. This parallels inconclusive findings from related work using the same analytic approach (Prati, 2024). It is possible that a twelve-month interval between waves of data is too long to observe accurate cross-lagged effects. Given this, finer grained data captured at shorter intervals is needed to confirm the precise temporality of this relationship. Nonetheless, the evidence from this chapter aligns with prior findings that have suggested the relationship is primarily concurrent (Butterworth et al., 2009; Butterworth et al., 2012; Kiely et al., 2015; Witteveen & Velthorst, 2020).

Perhaps of most pertinence, this chapter highlighted that much of the observed relationship between financial hardship and mental health is attributable to stable, trait-level differences between individuals, rather than momentary state-level within-person fluctuations over time. In other words, individuals who report experiencing greater hardship, also tend to be the same individuals reporting poorer mental health. This suggests that the relationship is more heavily driven by persistent structural differences between people, than momentary fluctuations in hardship experience or short-term changes in an individual's mental health.

This finding has important implications for preventative intervention. It suggests that temporary financial or mental health support may be less efficacious than policies that (1) improve social mobility and opportunities for socioeconomic attainment, (2) reduce intergenerational cycles of impoverishment, and (3) address factors related to housing affordability that may entrench and extend existing disparities in socioeconomic status and mental health.

Chapter 5 – The Association Between Long-term Profiles of Financial Hardship Experience, Latent Financial Hardship State Transitions, and Mental Health

Abstract

Background: The previous chapter employed random-intercept cross-lagged panel modelling (RI-CLPM) to clarify the bi-directional relationship between financial hardship and mental health. It focused on whether within-person changes in financial hardship were linked to concurrent or lagged changes in mental health (and vice-versa) and assessed the degree to which this relationship is attributable to stable, trait-level differences between individuals, or transient within-person fluctuations over time. This chapter demonstrated (1) a consistent negative relationship between concurrent financial hardship experience and mental health, and (2) that the majority of variability between financial hardship and mental health is attributable to stable, trait-level differences between individuals, rather than within-person changes over time. Thus, to further understand these results it is crucial to explicitly model these between-person differences.

Aims: This chapter aimed to explore the extent to which there exists distinct between-person profiles of financial hardship experience, and to analyse their relationship with mental health.

Methods: The sample analysed in this chapter comes from the ten most recent waves of the HILDA survey from 2014-2023. Complete case analysis gave a sample comprising a total of 14,429 households and 7,068 individuals (43.9% male / 56.2% female; average age = 50.5 years old), who contributed 70,680 person-wave observations over the ten-wave period. Social Sequence Analysis (SSA) was used to describe and visualise financial hardship experience within the sample. Latent Markov Modelling (LMM) was used to identify latent financial hardship states and mixed-effects logistic regression models were employed to assess how these latent states, and transitions between them, were related to mental health.

Results: The SSA identified two distinct clusters of financial hardship experience – a very large cluster of respondents who, largely did not experience financial hardship; and a much smaller cluster primarily composed of respondents who reported experiencing *both* subdimensions of financial hardship at each wave. The LMM analysis identified four distinct latent financial hardship states. Namely, 1. a 'very low risk' state; 2. a 'moderate cashflow

problems' state; 3. a 'moderate deprivation' state; and 4. a state comprising 'very high risk of both' cashflow problems and deprivation. A clear gradient in the risk of poor mental health was observed from state 1 (very low risk) to state 4 (very high risk of both). Moreover, transitions from a lower financial hardship risk state to a higher financial hardship risk state were all associated with an increasing risk of poor mental health.

Conclusion: This chapter identified distinct clusters of financial hardship experience, and distinct latent financial hardship states. The risk to mental health varied across the identified latent states and differed according to whether one moved from a state of lesser or greater financial hardship. The implications of these findings are discussed.

Introduction

Background

Building upon the first two analytic chapters of this thesis – which (1) synthesised prevailing international research examining the relationship between financial hardship, and (2) estimated the prevalence of financial hardship in Australia, and pooled 23 waves of longitudinal HILDA survey data to generate population-average estimates of associations with key sociodemographic correlates – the previous chapter of this thesis utilised the longitudinal structure of the HILDA survey, with longitudinal analytic techniques, to analyse the dynamics of the relationship between financial hardship and mental health over time. Specifically, random-intercept cross-lagged panel modelling (RI-CLPM) was employed to formally assess both longitudinal directional pathways operating between financial hardship and mental health, and to disaggregate stable between-person trait differences from wave-to-wave within-person state-based fluctuations.

The RI-CLPM analysis did not demonstrate clear evidence to support either a unidirectional or bidirectional within-person relationship between these two variables. More specifically, evidence was not found that was consistent with either *social causation* effects – whereby greater financial hardship was predictive of lower subsequent mental health – or *health selection* effects – whereby poorer mental health was predictive of greater levels of subsequent financial hardship. However, this analysis did reveal substantial differences in the share of variability accounted for by the between-and within-person components of this relationship. In particular, this analysis detailed that the majority of variability between financial hardship and mental health was attributable to stable, trait-level differences *between* individuals, as opposed to more transient wave-to-wave fluctuations occurring *within* individuals. In other words, people who generally reported greater levels of financial hardship, also tended to report poorer mental health. In contrast, when people reported greater financial hardship than their usual level, the effect on their mental health a year later was not overly pronounced. Similarly, when people reported poorer mental health than their usual level, the effect on their experience of financial hardship a year later was only very minor.

This finding prompts a natural follow-up question: what accounts for the substantial between-person differences in the association between financial hardship and mental health? It is to this question, that this chapter attends. In doing so, it aims to extend the previous analysis by explicitly modelling these between-person differences. In particular, this chapter classifies people according to the entirety of their financial hardship experience, identifies to what extent there exists distinct between-person profiles of financial hardship experience, describes and visualises these profiles, and examines to what degree they relate to mental health.

Life course Approaches

As its name suggests, the life course approach investigates how exposure to specific physical and social factors across key stages of life shapes long-term health outcomes (Ben-Shlomo & Kuh, 2002; Wagner et al., 2024). This approach is underpinned by the view that health outcomes reflect the complex interaction of the order, timing, duration, and accumulation of exposure to various health risk and protective factors across the life course. These include the socioeconomic conditions, family environment, biological traits, personal health behaviours, and broader cultural influences that characterise one's life-course (Ojima & Kondo, 2020; Wagner et al., 2024).

Accordingly, life course approaches can be used in epidemiology to identify and examine differences that emerge between individuals over time. By enabling observation of how social processes unfold across the life span, they help to discern whether individuals follow shared or distinct trajectories.

Within the life course framework, several theoretical causal models have emerged to provide mechanistic explanations of *how* varying exposures shape health outcomes in later life. These include the critical and sensitive period models, the accumulation of risk model, the pathway (or chain of risks) model, and the social mobility model (Mishra et al., 2015).

The sensitive period model explains how the impact of an exposure can vary depending on when it occurs. This model highlights how exposure to risk factors during specific periods of life – such as early childhood – can have a more severe or lasting impact on health and development than if experienced at other times (Ben-Shlomo & Kuh, 2002; Knudsen, 2004). Similarly, some exposures only demonstrate health impacts during specific spans of the life course – these moments are referred to as critical periods. Exposures during critical periods can have particularly damaging or permanent effects on development and subsequent health outcomes. However, outside of these critical periods, exposure poses no excess risk to health (Barker, 1986, 1995). The accumulation of risk model emphasises how the cumulative effect of repeated exposure to risk and protective factors shapes health outcomes in later life. This model considers the cumulative impact of illness and injury, harmful environmental conditions, and health-compromising behaviours. Accordingly, it positions health as the product of multiple risk factors that accumulate over time, whether through repeated or prolonged exposure over an extended duration (Hertzman & Power, 2003; Smith et al., 1997; Wadsworth, 1997). The pathway, or chain-of-risks model focuses on the sequential link between multiple exposures. This model highlights how exposure to one risk factor can increase the likelihood of exposure to another. In turn, it is the sequence of risk factors over the life course that leads to poor health outcomes (Lynch & Smith, 2005). Finally, the social mobility model considers how individuals transition between varying states of exposures. For example, individuals can move in and out of poverty, through varying states of employment, or gain greater levels of education. This model stresses that it is the overall direction of change in these transitions that shapes later disease risk (Hallqvist et al., 2004).

Life course research is enabled by large population-based longitudinal panel and birth-cohort studies that collect a wide range of social, economic, biological, and environmental data from the same respondents over many years (Wagner et al., 2024). It also relies upon specific analytic approaches to identify long-term patterns that unfold across successive waves of data collection. This chapter focuses on two such methods – namely social sequence analysis (SSA) and latent Markov modelling (LMM). In brief, SSA can provide a summary of the most common trajectories respondents follow with respect to particular factors. For example, SSA has commonly been used to model long-term patterns of education, employment, and family formation (McKetta et al., 2018). LMM on the other hand, can be used to identify the existence of hidden, or unobserved, latent processes in longitudinal data. It can also be used to estimate the probabilities associated with transitioning between identified latent states over time. The SSA and LMM approaches, as used in this chapter, are intended to test the social mobility model, with respect to how varying sequences of financial hardship experience, and transitions in latent financial hardship states, relate to mental health.

In recent years, a range of studies have used life course approaches to model long-term profiles of both socioeconomic disadvantage and health, in order to examine how they relate to each other. For example, (Sacker et al., 2013) estimated simultaneous changes in health and poverty dynamics for working-age adults from the British Household Panel Survey using a multiple-process latent transition model (MPLTM). They found concurrent and bidirectional longitudinal relationships between poverty and health. In particular, nonemployment was found to mediate the pathway operating from health to poverty and confound the reverse pathway from poverty to health. Similarly, Shin and colleagues (2025) used multi-channel sequence analysis over three waves of data from the US Health and Retirement study to model a series of material hardship trajectories, and examine their association with depressive symptoms and self-rated physical health. Their study demonstrated that persistent severe material hardship across multiple domains was associated with significantly higher depressive symptoms than minimal material hardship. A similar study by (Thomas, 2022) used latent class analysis and latent transition analysis to identify latent profiles of material hardship. Latent profiles were derived from families' experiences of needing to rely on free food or meals due to lack of money, losing housing or experiencing homelessness, inability to access needed medical care, having electricity, gas, oil, or telephone utilities shut off, and being unable to pay rent, mortgage, or utility bills. Multinomial logistic regression was then used to identify correlates of latent state membership. The study found that renting, partial tertiary education without degree completion, and income below 50% of the US federal poverty level were associated with membership in chronic hardship states, or with experiencing a longitudinal profile of worsening hardship.

In addition, several studies have used latent transition analysis and latent class analysis to model profiles of physical and mental health (Baumann et al., 2025; Chang et al., 2013; Fang et al., 2025). Lower income and lower educational attainment were consistently associated with occupying, and transitioning into, latent health states characterised by poorer health (Baumann et al., 2025; Chang et al., 2013). In contrast, remaining in states characterised by better health was associated with higher educational attainment (Chang et al., 2013). In relation to mental health, Fang and colleagues (2025) used latent transition analysis to demonstrate that lower income was associated with both membership, and transitions into, states characterised by lower psychological well-being.

To date, the extent to which distinct longitudinal profiles of financial hardship exist has not been examined with Australian data. Similarly, an analysis detailing the probability of moving between varying states of financial hardship in Australia has not been undertaken. Together, these analyses would provide important insights into typical long-term patterns of hardship in Australia, including the likelihood of moving into and out of financial hardship.

Aims

The broad aim of this chapter is to explore the extent to which there exists distinct between-person profiles of financial hardship experience and to analyse their relationship with mental health. More specifically, this chapter aims to (1) describe and visualise the experience of financial hardship, with respect to the order and timing of cashflow problems and deprivation across the ten waves of data; (2.1) explore whether meaningful latent financial hardship states could be identified; (2.2) utilise mixed-effects logistic regression models to assess the strength of the relationship between these latent states and mental health, and (2.3) assess the relationship between transitions from one latent financial hardship state to another and mental health.

Methods

Data

The analysis for this study used data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. A detailed explanation of the HILDA survey can be found in the General Introduction (Chapter 1) under the section titled *Data Sources*.

Sample

The sample analysed in this study uses the ten most recent waves (14-23; calendar years 2014-2023) of the Household, Income and Labour Dynamics in Australia (HILDA) survey. The HILDA Survey is a nationally representative household panel that has collected annual data on labour, family, income, and welfare dynamics since its inception in 2001 (Watson & Wooden, 2012). We removed all person-wave records that didn't comprise a completed Self-Completion Questionnaire (SCQ) and then retained all respondents who participated in all 10 waves. Finally, respondents missing financial hardship or mental health (MHI-5) data at any of the ten waves were removed from the analytic sample. This yielded a total of 14,429 households and 7,068 individuals.

Measures

The analysis in this study used measures of *sex* and *age*, *financial hardship*, and *mental health*. Details pertaining to how each of these items have been assessed and defined can be found in the General Introduction (Chapter 1) under the section titled *Data Sources*.

Analysis

All statistical analyses were conducted using R version 4.5.0 (R Core Team, 2025). Descriptive analyses were conducted to examine the prevalence of cashflow problems and deprivation, and their co-occurrence at each time point within the sample. Social sequences analysis (SSA) was employed to provide a comprehensive descriptive and visual overview of financial hardship profiles and their temporality across the ten waves of analysis. Latent Markov Modelling (LMM) was then used to gain a finer grained understanding of the impact to mental health of transitions between latent financial hardship states at successive timepoints. Finally, mixed-effects logistic regression models were estimated to assess the relationship between the latent states identified from the latent Markov modelling analysis and mental health, and to assess the relationship between latent state transitions and mental health. An individual-level random intercept was included in all mixed-effects logistic regression models to account for the correlation between repeated observations from the same respondents. The social sequence analysis was conducted using the *TraMineR* (Gabadinho et al., 2011) and *cluster* (Rousseeuw et al., 2013) packages in R. The Latent Markov Modelling analysis was conducted using the *LMest* (Bartolucci et al., 2017) package in R.

Social Sequence Analysis (SSA)

Broadly, social sequence analysis compares respondents' life-course trajectories with respect to defined states across a selected set of variables. In turn, individuals sharing similar trajectories are grouped together. SSA was used to generate sequences for every respondent according to their unique experience of cashflow problems and deprivation, across all ten annual waves of data.

A four-category variable was constructed according to respondents' experiences of cashflow problems and deprivation at each wave. Specifically, individuals who reported neither cashflow problems nor deprivation in a wave were coded as "N" (neither). Respondents indicating cashflow problems were coded as "C" (cashflow problems), while those reporting deprivation were coded as "D" (deprivation). Respondents who reported experiencing both cashflow problems and deprivation within the same wave were coded as "B" (both).

Optimal matching was used to compute pairwise distances between each respondent's individual hardship sequence. Optimal matching determines the extent to which sequences are different from each other, and in turn, how much one sequence would need to transform, or mutate, to resemble the other sequence. Thus, optimal matching compares the individual sequences to each other to determine how close or far away one respondent's sequence is from another's (Abbott & Tsay, 2000). The goal of optimal matching is to expend as little effort as possible aligning each sequence – in other words, the goal is to determine the *minimum* distance between them (Cornwell, 2015). This 'sequence alignment' step takes into account each sequence's similarity with respect to the elements they contain, and their similarity with respect to how the elements are ordered. Sequence alignment is completed using distinct operations – namely, 'substitutions' and 'indels'. Substitution involves replacing individual sequence elements from one to another. Indel involves inserting or deleting elements to/from a sequence to align it with another.

To quantify the extent to which sequences need to be transformed a "penalty", or "cost", is assigned to each manipulation that is performed. In turn, the total number of these manipulations is summed, and the resulting value is treated as the degree of difference, dissimilarity, or "distance" between the sequences being compared. In other words, the higher the number of manipulations, the greater the dissimilarity or distance between sequences. There are several different ways of quantifying this distance, which are dependent on the transformation operations used, and the cost assigned to making each of them[34].

This analysis used an 'expert' approach to optimal matching. Rather than using an arbitrary or data driven approach to assigning transformation costs, the expert approach involves the researcher explicitly defining costs for sequence alignment operations that are theoretically informed and reflect the meaning of underlying transitions between states. In line with this, a substitution cost matrix was generated that ordered transitions from lowest risk financial hardship to highest risk financial hardship. Transitions from no hardship to cashflow problems were ordered as least risk (1), followed by a transition from cashflow problems to deprivation (2), and then deprivation to both cashflow problems and deprivation (3). This ordering was informed by prior work that has suggested that cashflow problems represent a more common, but less severe form of financial hardship than deprivation (Bray, 2001). The matrix containing all substitution costs is provided in

[34] For a detailed discussion on the various approaches to optimal matching see chapter 5, pages 109-129 of Cornwell (2015).

Table 19. Indel costs were set at 1.5.

Drawing upon this dissimilarity matrix, Ward's hierarchical clustering was used to condense all respondents' sequences into one of a series of clusters. The final number of clusters was chosen after considering average silhouette width (ASW), the Point Biserial Correlation (PBC), Hubert's Gamma (HG), R^2, and cluster sample sizes. The PBC and HG produce scores ranging from -1 to 1, which measure the correlation between a given dissimilarity matrix and a binary (0-1) vector – where 0 is assigned to pairs of sequences in the same cluster, and 1 is assigned to sequences in different clusters. A correlation approaching 1 indicates a valid partition, where the 'distances' within cluster pairings tend to be smaller than those between clusters (Studer, 2013). Average silhouette width (ASW) is a way of visualising how much of the variance is explained by the number of clusters selected. ASW is also a measure of how similar observations are to observations within their cluster relative to observations outside their cluster (Rousseeuw, 1987). Kaufman & Rousseeuw (2005)[35] recommend that coefficients between 0.70 and 1.00 represent 'strong structure', coefficients between 0.51 and 0.70 represent 'reasonable structure', coefficients between 0.26 and 0.50 represent 'weak structure', and coefficients less than 0.25 represent 'no structure'. Cluster solutions from $k = 2$ to $k = 10$ were evaluated to determine which number best explained the observed data. Entropy scores were used to assist with characterisation of clusters in the selected solution. Entropy scores are a measure of the cross-sectional diversity of states, at any given point in time. When assessing at the cluster level, an entropy score of 0 means there is no diversity, and every respondent is occupying the same state. In contrast, an entropy score of 1 occurs when the same proportion of cases occupy each state (Gabadinho et al., 2011).

[35] This information is found in Table 4 on page 88 of Kaufman & Rousseeuw (2005). Additional detail on using silhouette width can be found in the adjoining pages.

Table 19
'Expert' defined substitution cost matrix

	N	***C***	***D***	***B***
N	0	1	2	3
C	1	0	1	2
D	2	1	0	1
B	3	2	1	0

N = Neither cashflow problems nor deprivation;
C = Cashflow problems;
D = Deprivation;
B = Both Cashflow problems and Deprivation

Latent Markov Modelling (LMM)

Latent Markov modelling (LMM) – as introduced by Wiggins in 1955 (Wiggins, 1955, 1973) – is a probabilistic approach to identifying the existence of hidden, or unobserved, latent processes in longitudinal data. LMM is an extension of latent class analysis (LCA), specifically designed for use with longitudinal data, to characterise longitudinal processes (Vermunt, 2004). In short, LCA posits that an underlying grouping variable (i.e., a latent class variable) is not observed, but can be inferred from a set of categorical indicators (Goodman, 1974). Akin to this, LMM relates a set of *observed* responses – in this case, indicators of financial hardship – to an *unobserved* categorical latent variable, and in turn classifies respondents into distinct subgroups (Rabe-Hesketh & Skrondal, 2008). However, unlike LCA, where the resultant classes represent a stable set of characteristics or behaviours, the longitudinal structure of LMM allows individuals to transition between different subgroups over time. This form of LMM is known as Latent Transition Analysis (LTA). Given that subgroup membership is not assumed to be stable over time, the term "latent states" is used to refer to the resultant distinct subgroups, as opposed to the term "latent classes" (which is used in LCA).

More specifically, LMM assumes that an unobserved latent process progresses over time via a Markov chain. In other words, a *first-order* Markov assumption holds that the probability of occupying a particular state at time $t + 1$, depends solely on the state occupied at time t. Secondly, the unobserved latent process is also assumed to influence the distribution of the observed response(s). Related to this second assumption is the idea of *local independence*, which means that the observed response(s) are assumed to be conditionally independent, given the unobserved latent process. In other words, once state membership is known, the observed response(s) do not provide any additional information – i.e., the underlying latent process fully explains the observed response(s). LMM comprises two key components which are modelled simultaneously – (1) a measurement model, which defines the probability of experiencing the observed responses, given the latent process; and (2) a latent model, which defines how states are distributed and evolve over time.

Three sets of parameters are estimated in LMM to describe the relationship between the unobserved (latent) variables across time points. First, a set of item-response probabilities are estimated. Broadly, and in the words of (Lanza et al., 2010), these 'reflect the correspondence between the observed indicators of the latent variable at each time period and latent status membership'. Put simply, and with reference to this work, the item-response probabilities reflect the probability of reporting cashflow problems and deprivation within each latent state. Second, latent state membership probabilities are estimated – this comprises a matrix containing the marginal distribution of the latent states – in other words, the proportion of individuals in each latent financial hardship state, at each time point. Finally, transition probabilities – these reflect the probability of transitioning from one latent state to another between time *t* and time *t*+1.

Model Specification

Multivariate latent Markov modelling was employed to identify the existence of latent financial hardship states, and to model the probability of transitioning between them. All estimated latent models were fitted to two observed binary variables, namely cashflow problems (yes/no) and deprivation (yes/no)[36]. In turn, this approach defines the probability of endorsing cashflow problems and deprivation within each of the identified latent states. Importantly this approach assumes local independence of the observed variables used to fit the model. Put concretely, once a respondent's latent financial hardship state is identified for a given time-period, it is assumed that this accounts for any apparent correlation between cashflow problems and deprivation.

Model estimation seeks to determine the set of parameters that define the global maximum of the likelihood function. This process proceeds by maximum likelihood, using the expectation-maximisation (EM) algorithm (Bartolucci et al., 2017). Additionally, all models were constructed using first-order Markov chains, meaning the latent state at time *t* was only dependent on the latent state at time *t* - 1.

To mitigate sub-optimal model fit, which can occur due to convergence upon local maxima, all models were estimated using 15 random starts per *k*. Additionally, all models evaluated *k* = 2-10 latent states to identify the optimal number.

Models comprising time-varying and time-homogeneous transition probabilities were estimated. A time-varying model estimates separate transition probabilities between each adjacent time-point. Conversely, a time-homogeneous model estimates a single set of

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[36] It should be noted that the use of two binary variables (cashflow problems and deprivation) to fit the latent Markov model differed to the single, four-category variable used in the SSA. This was principally due to the complexity of conducting a multi-channel SSA being beyond the scope of this chapter.

transition probabilities that applies across all waves. Initially, models (k = 2-10) comprising time-varying transition probabilities between adjacent waves were estimated. The optimal number of states was selected according to the Bayesian Information Criterion (BIC). This time-varying solution was then compared to a series of models (k = 2-10) estimated with time-homogeneous transition probabilities. Again, the optimal solution was selected according to the BIC.

Following model fit, the latent financial hardship state was estimated for all respondents at each time-point using local decoding. Decoding refers to the process by which the observed data is used to predict the sequence of latent states occupied by each respondent. This can take the form of both *global*, and *local*, decoding. In local decoding the posterior probabilities – estimated using the expectation maximisation algorithm – are used to obtain a prediction of the latent state for each respondent at each time point (Bartolucci et al., 2017).

Following decoding, variables were constructed for each of the four states to detail which latent state a respondent occupied at time t, and which latent state they transitioned to at time t+1, such as ‘state 1 to state 2’, or 'state 2 to state 3’. This information was then used to explore associations between state, and state transitions, with mental health using a series of multivariable mixed-effects regression models. Specifically, model 1 assessed the degree to which transitions from the very low risk state, to all other states, were associated with mental health, while controlling for prior mental health at the initial very low risk state. Model 2 assessed the relationship between state transitions from the moderate cashflow problems state with mental health, while controlling for prior mental health at the initial moderate cashflow problems state. Model 3 assessed the relationship between state transitions from the moderate deprivation state with mental health, while controlling for prior mental health at the initial moderate deprivation state. Model 4 assessed the relationship between state transitions from the very high risk of both state with mental health, while controlling for prior mental health at the initial very high risk of both state. The final model assessed the overall relationship between latent financial hardship state and mental health.

Results

Table 20 provides the number of households and individuals comprising the analytic sample each year. In total, the 7,068 individuals (43.9% male / 56.2% female; average age = 50.5 years old) contributed 70,680 person-wave observations over the ten-wave period. Table 21 details the distribution of financial hardship experienced within the sample across the ten waves of analysis. Selection into the analytic sample were assessed by comparing the baseline (wave 14) sociodemographic characteristics of respondents with complete data at all ten waves between 2014 and 2023, to those without complete data across this period (Appendix D.1). Respondents in the analytic sample were more likely to be female, middle-aged, hold higher educational qualifications, reside in higher income households, experience less financial hardship, and be in better physical and mental health.

Descriptive Cross-Sectional Analyses

Table 22 presents the prevalence of cashflow problems and deprivation, and their co-occurrence at each of the ten assessed annual time points. The proportion of the sample reporting no experience of financial hardship at all ranged from 81.2% to a maximum of 86.1%. The most common form of hardship was cashflow problems, ranging between 7.1% to 10.4%, followed by the co-occurrence of cashflow problems and deprivation which ranged from 4.3% to 6.1%. The prevalence of deprivation alone was the lowest at all time points, ranging between 2.1% and 3.0%.

Table 20
Analytic sample details with respect to sex and age

Characteristic	n (Obs.)	%
Sample		
Respondents	70,680	
Households	14,429	
Sex		
Male	30,990	43.9
Female	39,690	56.2
Age Cat		
15-19	1,120	1.6
20-29	7,988	11.3
30-39	11,827	16.7
40-49	12,351	17.5
50-59	14,304	20.2
60-69	12,822	18.1
70+	10,268	14.5

Table 21
Number and proportion of respondents reporting 1-10 waves of any financial hardship, cashflow problems, deprivation, and both cashflow problems and deprivation

	FH (Any)		Cashflow Probs.		Deprivation		Both CF and Dep	
Waves of FH	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
0	3,784	53.5	4,124	58.4	5,204	73.6	5,742	81.2
1	1,126	15.9	1,073	15.2	738	10.4	530	7.5
2	528	7.5	465	6.6	348	4.9	242	3.4
3	343	4.9	333	4.7	185	2.6	156	2.2
4	290	4.1	277	3.9	157	2.2	110	1.6
5	208	2.9	184	2.6	106	1.5	85	1.2
6	203	2.9	164	2.3	92	1.3	59	0.8
7	177	2.5	128	1.8	71	1.0	48	0.7
8	130	1.8	114	1.6	60	0.9	37	0.5
9	109	1.5	97	1.4	50	0.7	31	0.4
10	170	2.4	109	1.5	57	0.8	28	0.4

Table 22

Prevalence of cashflow problems, deprivation, and their co-occurrence, at each annual time point

		No FH		**Only Cashflow Problems**		**Only Deprivation**		**Both CF and Dep**	
Wave	**Total**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
14	7,068	5,738	81.2	735	10.4	174	2.5	421	6.0
15	7,068	5,820	82.3	651	9.2	171	2.4	426	6.0
16	7,068	5,903	83.5	607	8.6	148	2.1	410	5.8
17	7,068	5,899	83.5	634	9.0	159	2.3	376	5.3
18	7,068	5,875	83.1	593	8.4	172	2.4	428	6.1
19	7,068	5,884	83.3	562	8.0	202	2.9	420	5.9
20	7,068	5,970	84.5	522	7.4	215	3.0	361	5.1
21	7,068	6,031	85.3	535	7.6	170	2.4	332	4.7
22	7,068	6,086	86.1	499	7.1	181	2.6	302	4.3
23	7,068	5,885	83.3	555	7.9	212	3.0	416	5.9

* CF = Cashflow problems; Dep = Deprivation

Sequence Analysis

Across the sample of 7,068 respondents, a total of 1,658 person-unique sequences were identified. The sequence comprising no financial hardship at all 10 waves was, by far, the most common sequence. This sequence was shared by 3,784 respondents, accounting for 53.5% of all respondents. Furthermore, Table 23 details the 20 most common sequences shared by respondents in the sample, accounting for 68.1% of all sequences. Notably, 18 of these sequences are characterised by only one wave of hardship, while one sequence (rank 15) comprised respondents experiencing both hardship subdimensions (cashflow problems and deprivation) over all ten waves.

Table 24 details ASW coefficients, along with values for Point Biserial Correlation (PBC), Hubert's Gamma (HG) and R^2 for each of the k = 2-10 clusters solutions assessed from the 'expert' optimal matching approach. ASW (0.79), PBC (0.79) and HG (0.99) all provided support for a two cluster solution.

Figure 9 provides a visual distribution of the states comprising each of the two clusters, while Figure 10 provides a sequence index plot highlighting all sequences contained within each cluster. Table 25 details the average mental health scores (SF-36) by the two clusters over time.

The first cluster (n = 6,659; 94.2%) was primarily composed of respondents who did not experience financial hardship (ranging from 85.0% to 90.4% each wave). This cluster stability was further reflected in the low entropy values each wave (0.29 to 0.4). Average SF-36 mental health scores in this cluster ranged between 76.0 and 73.6. However, the second cluster (n = 409; 5.8%) was primarily composed of respondents who reported experiencing both subdimensions of financial hardship at each wave (ranging from 48.0% to 64.3%). To a smaller degree, this cluster also comprised respondents experiencing only cashflow problems (12.0% to 20.5%), and only deprivation (9.5% to 18.0%). Given this, cluster 2 was marked by very high entropy (0.74 to 0.91). Average SF-36 mental health scores from 60.2 to 55.9 and demonstrated a very slight decreasing trend over time. Detailed wave to wave state proportions and entropy values are provided in Appendix D.2.

Table 23
Frequency table of the 20 most common sequences across all ten waves of analysis

Sequence	Rank	n	%	Cum. %
N/10	*1*	3,784	53.5	53.5
C/1-N/9	*2*	116	1.6	55.2
N/6-C/1-N/3	*3*	115	1.6	56.8
N/7-C/1-N/2	*4*	115	1.6	58.4
N/9-C/1	*5*	88	1.3	59.7
N/8-C/1-N/1	*6*	75	1.1	60.8
N/1-C/1-N/8	*7*	61	0.9	61.6
N/4-C/1-N/5	*8*	57	0.8	62.4
N/5-C/1-N/4	*9*	56	0.8	63.2
N/3-C/1-N/6	*10*	55	0.8	64.0
N/2-C/1-N/7	*11*	51	0.7	64.7
N/6-D/1-N/3	*12*	31	0.4	65.2
D/1-N/9	*13*	30	0.4	65.6
N/9-D/1	*14*	30	0.4	66.0
B/10	*15*	28	0.4	66.4
N/8-D/1-N/1	*16*	27	0.4	66.8
N/7-D/1-N/2	*17*	26	0.4	67.1
N/1-D/1-N/8	*18*	23	0.3	67.5
N/9-B/1	*19*	23	0.3	67.8
C/2-N/8	*20*	21	0.3	68.1

N = None (i.e., no financial hardship); C = Cashflow Problems; D = Deprivation; B = Both Cashflow Problems and Deprivation

Table 24
Average silhouette width (ASW), Point Biserial Correlation (PBC), Hubert's Gamma (HG), and R^2 (Variance) of k = 2-10 cluster solutions – 'Expert' approach

k	**ASW**	**PBC**	**HG**	**R^2**
2	0.79	0.79	0.99	0.29
3	0.68	0.76	0.96	0.44
4	0.67	0.77	0.97	0.46
5	0.66	0.77	0.97	0.47
6	0.66	0.77	0.97	0.48
7	0.66	0.77	0.97	0.49
8	0.63	0.78	0.97	0.50
9	0.63	0.78	0.97	0.51
10	0.52	0.69	0.93	0.53

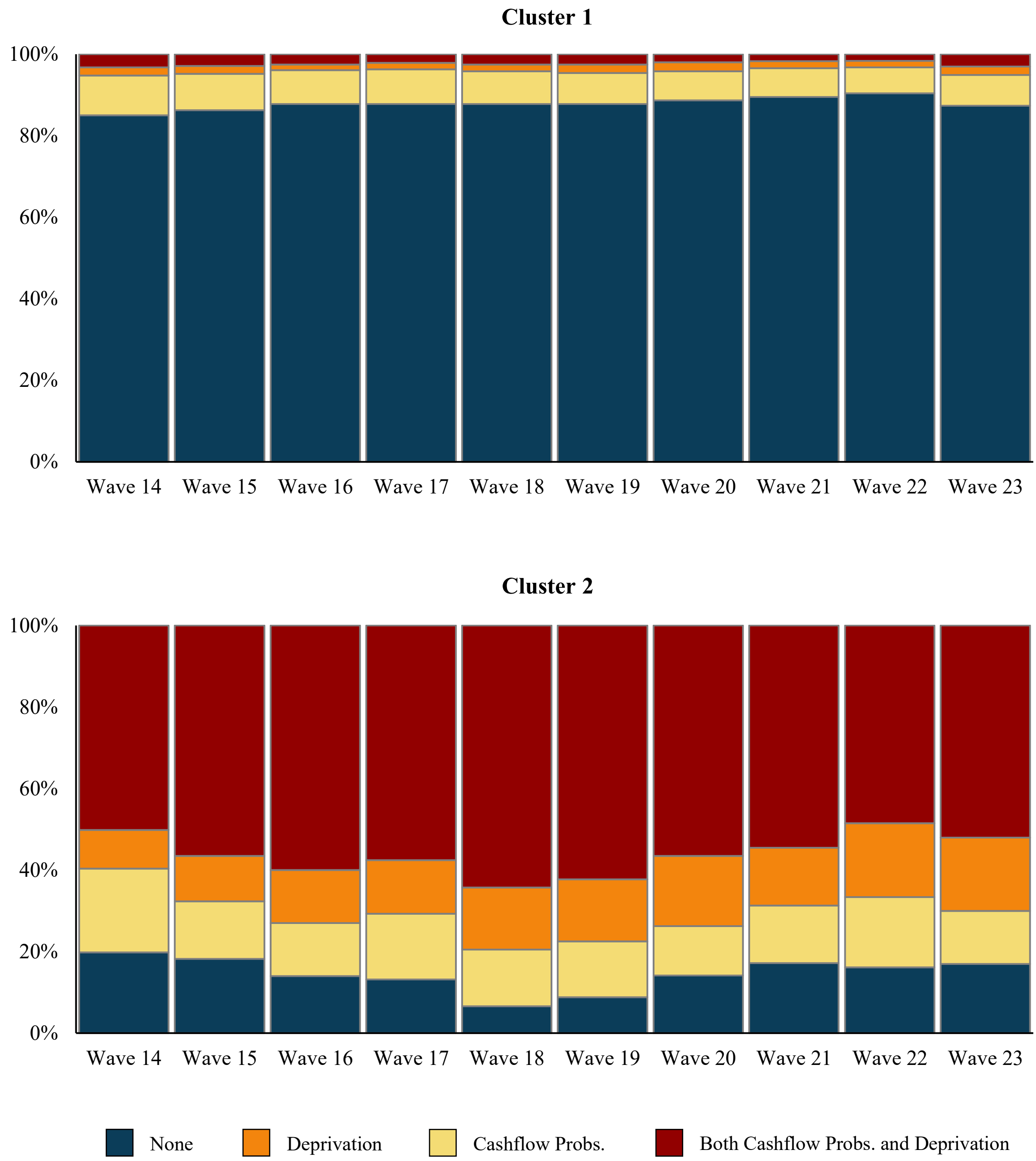

Figure 9

State Distribution Plot – $k = 2$

Proportion of respondents occupying each state by wave

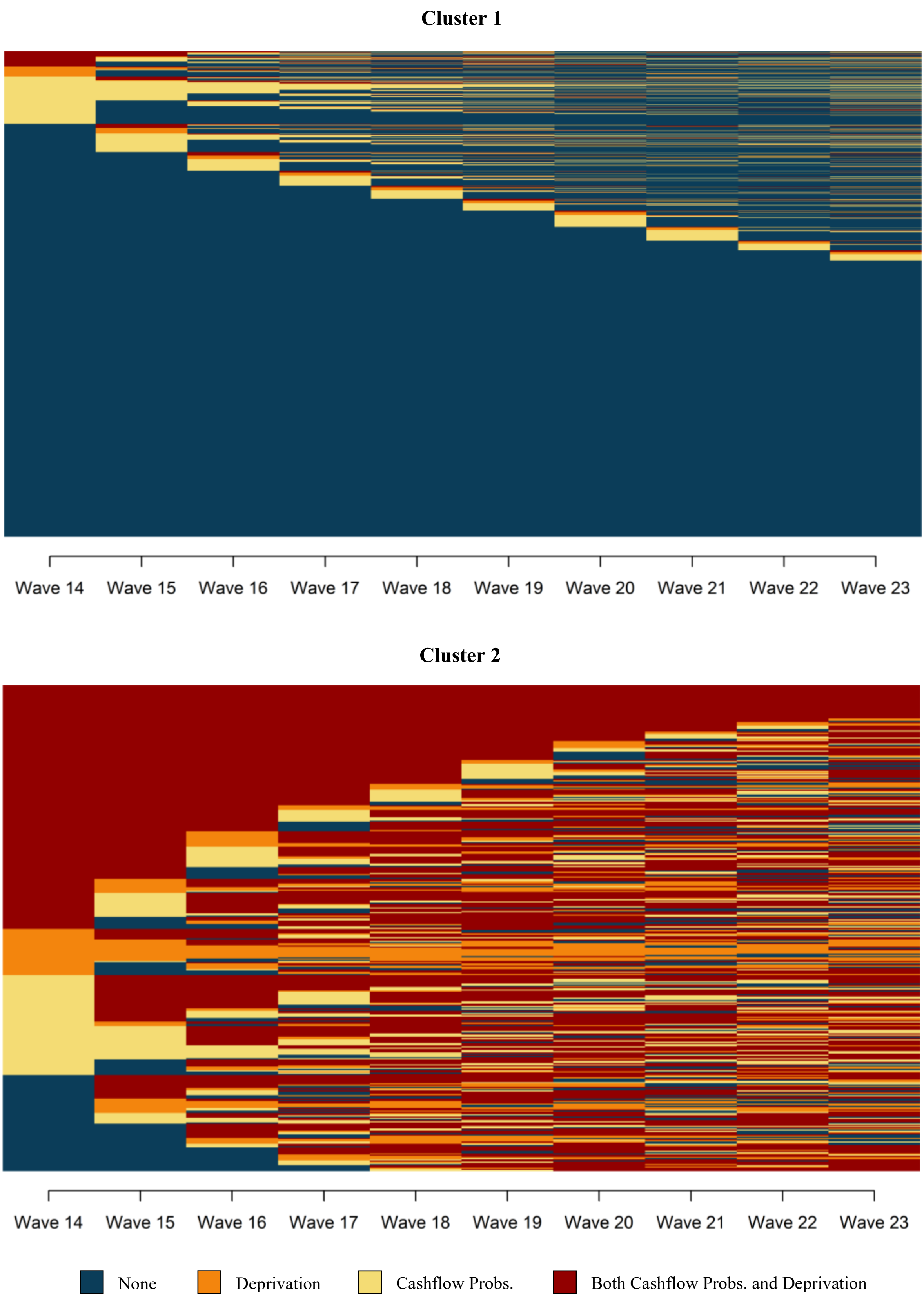

Figure 10

Sequence Index Plot – $k = 2$

Reading from left to right of the two figures, each row on the y-axis represents the sequence of financial hardship states experienced by each respondent between wave 14 and wave 23.

Table 25
Average mental health (SF-36) and interquartile range by cluster, from 2014 to 2023

	Cluster 1		Cluster 2	
Year	**Mean (SD)**	**Q_1 - Q_3**	**Mean (SD)**	**Q_1 - Q_3**
2014	76.0 (16.1)	68-88	60.2 (21.5)	44-80
2015	75.8 (16.1)	68-88	58.2 (21.0)	44-76
2016	75.9 (16.2)	68-88	57.8 (20.9)	44-76
2017	75.7 (16.2)	68-88	58.7 (20.4)	48-76
2018	75.6 (16.2)	68-88	57.6 (21.3)	44-76
2019	75.4 (16.4)	68-88	57.6 (20.8)	44-72
2020	74.1 (16.7)	64-88	55.9 (20.2)	44-72
2021	73.6 (17.1)	64-88	56.3 (20.8)	40-72
2022	74.0 (16.8)	64-88	56.2 (21.5)	44-72
2023	73.9 (16.7)	64-88	57.2 (21.2)	44-76

Latent Markov Modelling

Time-heterogeneous and time-homogeneous Latent Markov models comprising 2 to 10 states were estimated. Final model selection was informed by statistical fit and substantive model interpretability. Specifically, candidate models were initially identified by model fit statistics. In turn, item-response probabilities were examined to ascertain whether additional latent states represented substantively distinct forms of hardship or merely finer gradations of existing states.

Fit indices (BIC, AIC, and log-likelihood) for all assessed models (k = 2-10) are detailed in Table 26. Of the assessed time-heterogeneous models, the lowest BIC was obtained for a 4-state solution (BIC = 65,819.74). However, within the assessed time-homogeneous models, the lowest BIC was obtained for an 8-state solution (BIC = 64,596.63). Closer inspection of the 5- to 8-state time-homogeneous models revealed substantial overlap between latent financial hardship states. More specifically, these additional latent states were characterised by only minor gradations in the probability of experiencing cashflow problems and deprivation, as opposed to substantive, qualitative differences. Given this, the 4-state time-homogeneous solution was chosen as it represented a compromise between optimal model fit, parsimony, and interpretability, while still capturing the main latent profile structure. Moreover, this 4-state time-homogeneous solution demonstrated a lower BIC than each of the time-heterogeneous solutions. While model comparison testing suggested that the time heterogeneous model provides better model fit, the BIC provided very strong support for the time-homogeneous model (Table 27). In the interests of transparency, summary statistics, item-response probabilities, state proportions over time, and transition probability matrices for the aforementioned 4-state time-heterogeneous solution are detailed in Appendix D.3. Similarly, details of the 8-state time-homogeneous solution, including item-response probabilities, state proportions, and transition probability matrices are provided in Appendix D.4.

The states comprising the 4-state time-homogeneous solution were characterised by the probability of endorsing experience of cashflow problems and deprivation. Item response probabilities for these four states are detailed in Table 28. Specifically, the four latent states were defined as *very low risk* – defined by a near zero probability of endorsing cashflow problems (2.0%) and deprivation (0.6%); *moderate cashflow problems* – defined by a 55.8% chance of experiencing cashflow problems and 7.6% chance of experiencing deprivation;

moderate deprivation – defined by a 40.7% chance of experiencing deprivation and 13.3% chance of cashflow problems; and *very high risk of both* – defined by a 96.8% chance of cashflow problems, and an 85.6% chance of experiencing deprivation.

Table 26
Fit indices for all assessed time heterogeneous, and time homogeneous models (k = 2-10)

	Time Heterogeneous			Time Homogeneous		
k	**BIC**	**AIC**	**logLik**	**BIC**	**AIC**	**logLik**
2	68,979.44	68,821.58	-34,387.79	68,937.44	68,889.40	-34,437.70
3	66,788.26	66,362.73	-33,119.37	66,537.07	66,440.98	-33,206.49
4	65,819.74	65,003.01	-32,382.50	65,183.80	65,025.94	-32,489.97
5	65,905.67	64,574.18	-32,093.09	64,794.01	64,560.66	-32,246.33
6	66,444.21	64,474.43	-31,950.22	64,611.88	64,289.30	-32,097.65
7	67,240.52	64,508.91	-31,856.46	64,663.16	64,237.63	-32,056.82
8	68,288.76	64,671.78	-31,808.89	64,596.63	64,054.42	-31,948.21
9	69,468.82	64,842.93	-31,747.47	64,689.65	64,017.05	-31,910.52
10	70,775.18	65,016.85	-31,669.42	64,831.85	64,015.11	-31,888.56

Table 27
Model fit comparison – Time heterogeneous vs time homogeneous models (k = 4)

Model	Loglik	df	χ^2	AIC	BIC	$\Delta\chi^2$	Δdf	p-value
Heterogeneous	-32,383	119	64,765	65,003.01	65,819.74	—	—	—
Homogeneous	-32,490	23	64,980	65,025.94	65,183.80	214.92	96	0.000

Table 28
Item-Response Probabilities

	State			
Item	Very Low Risk	Mod. Cashflow Problems	Mod. Deprivation	Very High Risk - Both
Cashflow Problems	2.0%	55.8%	13.3%	96.8%
Deprivation	0.6%	7.6%	40.7%	85.6%

The proportion of the sample occupying each state is detailed in Table 29 and highlighted in Figure 11. At all assessed time points, latent state membership was highest in the *very low risk* state, with the proportion of the sample occupying this state increasing over time from 75.6% in 2014 to 79.4% in 2023. Membership in the *moderate cashflow problems* state decreased from 14.2% in 2014 to 9.7% in 2023, whereas membership in the *moderate deprivation* state increased over this same period from 4.1% in 2014 to 5.9% in 2023. Finally, membership in the *very high risk of both* state decreased from 6.2% in 2014 to 5.0% in 2023.

Table 30 details the person-years in each latent state by key demographic factors, pooled across all ten waves of analysis. Percentages represent column proportions to provide composition of each state. For comprehensiveness, the corresponding table containing row proportions is provided in Appendix D.5. Across the total 70,680 person-years, 79.8% were in the very low risk state (n = 56,424), 10.5% were in the moderate cashflow problems state (n = 7,407), 4.4% were in the moderate deprivation state (n = 3,116), and 5.3% were in the very high risk of both state (n = 3,733).

Table 29

Latent state membership probabilities at each time point

State	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Very Low Risk	0.756	0.762	0.768	0.774	0.778	0.782	0.786	0.789	0.792	0.794
Mod. Cashflow Problems	0.142	0.133	0.126	0.119	0.114	0.109	0.105	0.102	0.099	0.097
Mod. Deprivation	0.041	0.045	0.049	0.052	0.054	0.055	0.057	0.058	0.058	0.059
Very High Risk - Both	0.062	0.059	0.057	0.056	0.054	0.053	0.052	0.052	0.051	0.050

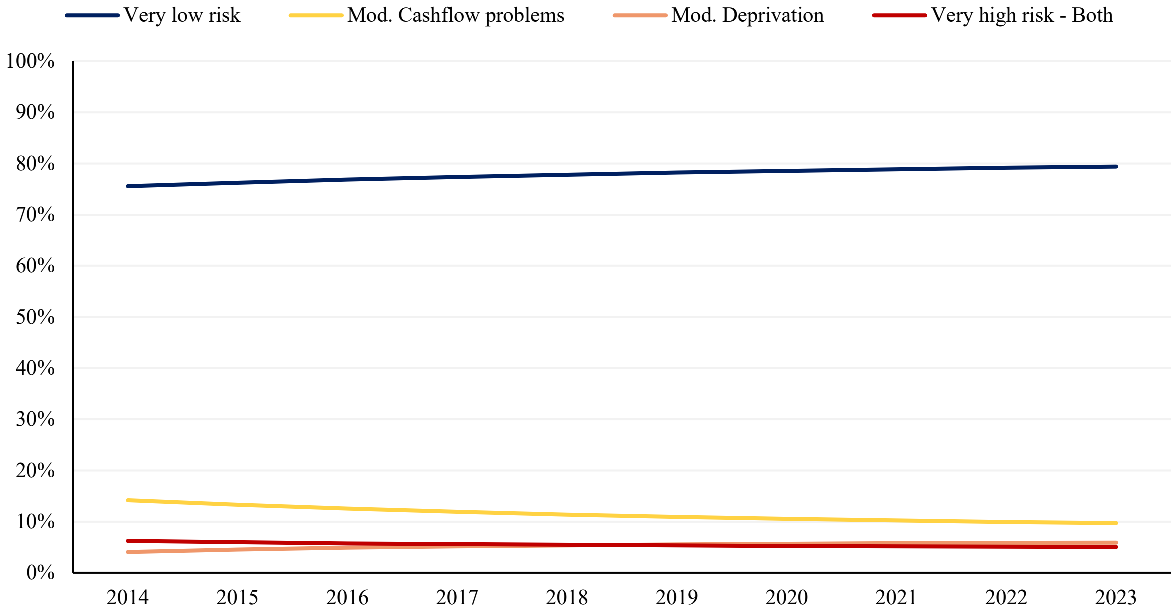

Figure 11
Latent state membership probabilities at each time point

Table 30

Person-years in each latent state by key demographic factors

Pooled across all ten annual waves of analysis

Characteristic	Total (n)	1 (n)	2 (n)	3 (n)	4 (n)	1 (%)	2 (%)	3 (%)	4 (%)
Sex									
Male	30,990	25,586	2,782	1,354	1,268	*45.4*	*37.6*	*43.5*	*34.0*
Female	39,690	30,838	4,625	1,762	2,465	*54.7*	*62.4*	*56.6*	*66.0*
Age Category									
15-19	1,120	937	98	50	35	*1.7*	*1.3*	*1.6*	*0.9*
20-29	7,988	5,552	1,415	342	679	*9.8*	*19.1*	*11.0*	*18.2*
30-39	11,827	8,545	1,723	553	1,006	*15.1*	*23.3*	*17.8*	*27.0*
40-49	12,351	9,255	1,687	557	852	*16.4*	*22.8*	*17.9*	*22.8*
50-59	14,304	11,506	1,441	681	676	*20.4*	*19.5*	*21.9*	*18.1*
60-69	12,822	11,208	661	592	361	*19.9*	*8.9*	*19.0*	*9.7*
70+	10,268	9,421	382	341	124	*16.7*	*5.2*	*10.9*	*3.3*
Birth Cohort									
1990-2009	8,358	5,999	1,312	400	647	*10.6*	*17.7*	*12.8*	*17.3*
1970-1989	24,334	17,898	3,495	1,088	1,853	*31.7*	*47.2*	*34.9*	*49.6*
1950-1969	27,344	22,722	2,212	1,300	1,110	*40.3*	*29.9*	*41.7*	*29.7*
1930-1949	10,506	9,689	384	315	118	*17.2*	*5.2*	*10.1*	*3.2*
1900-1929	138	116	4	13	5	*0.2*	*0.1*	*0.4*	*0.1*
SEIFA									
5 (Greatest Advantage)	14,141	12,447	1,046	364	284	*22.1*	*14.1*	*11.7*	*7.6*
4	14,969	12,463	1,420	517	569	*22.1*	*19.2*	*16.6*	*15.2*
3	14,484	11,624	1,609	581	670	*20.6*	*21.7*	*18.7*	*18.0*
2	14,000	10,813	1,609	693	885	*19.2*	*21.7*	*22.2*	*23.7*
1	13,037	9,046	1,718	955	1,318	*16.0*	*23.2*	*30.7*	*35.3*
NA	49	31	5	6	7	*0.1*	*0.1*	*0.2*	*0.2*
Education									
Postgrad	5,601	5,049	364	100	88	*9.0*	*4.9*	*3.2*	*2.4*
Undergrad	18,359	15,678	1,540	646	495	*27.8*	*20.8*	*20.7*	*13.3*
Diploma/Vocational	23,924	18,103	2,875	1,289	1,657	*32.1*	*38.8*	*41.4*	*44.4*
Year 12	9,350	7,027	1,258	387	678	*12.5*	*17.0*	*12.4*	*18.2*
Year 11 or below	13,426	10,547	1,370	694	815	*18.7*	*18.5*	*22.3*	*21.8*
Undetermined	20	20	NA	NA	NA	*0.0*	*NA*	*NA*	*NA*
Employment									
Full Time	30,436	24,968	3,490	955	1,023	*44.3*	*47.1*	*30.7*	*27.4*
Part Time	15,539	12,057	1,937	634	911	*21.4*	*26.2*	*20.4*	*24.4*
Unemployed	1,607	853	252	185	317	*1.5*	*3.4*	*5.9*	*8.5*
Not in labour force	23,098	18,546	1,728	1,342	1,482	*32.9*	*23.3*	*43.1*	*39.7*
Income Quintile (Household)									
5 (Highest)	19,585	17,990	1,044	316	235	*31.9*	*14.1*	*10.1*	*6.3*
4	17,121	14,297	1,847	522	455	*25.3*	*24.9*	*16.8*	*12.2*
3	14,067	10,555	2,032	622	858	*18.7*	*27.4*	*20.0*	*23.0*
2	12,447	8,626	1,639	932	1,250	*15.3*	*22.1*	*29.9*	*33.5*
1	7,460	4,956	845	724	935	*8.8*	*11.4*	*23.2*	*25.1*
Physical Functioning (SF-36)									
91-100	36,468	30,114	3,830	1,123	1,401	*53.4*	*51.7*	*36.0*	*37.5*
81-90	12,833	10,505	1,233	516	579	*18.6*	*16.7*	*16.6*	*15.5*
71-80	6,474	5,177	636	289	372	*9.2*	*8.6*	*9.3*	*10.0*
61-70	4,083	3,099	450	246	288	*5.5*	*6.1*	*7.9*	*7.7*
51-60	2,813	2,073	310	191	239	*3.7*	*4.2*	*6.1*	*6.4*
41-50	2,438	1,652	304	222	260	*2.9*	*4.1*	*7.1*	*7.0*
31-40	1,687	1,150	190	169	178	*2.0*	*2.6*	*5.4*	*4.8*
21-30	1,396	915	155	136	190	*1.6*	*2.1*	*4.4*	*5.1*
11-20	1,010	673	132	103	102	*1.2*	*1.8*	*3.3*	*2.7*
0-10	900	600	110	92	98	*1.1*	*1.5*	*3.0*	*2.6*
NA	578	466	57	29	26	*0.8*	*0.8*	*0.9*	*0.7*
Mental Health (SF-36)									
91-100	11,718	10,722	643	213	140	*19.0*	*8.7*	*6.8*	*3.8*
81-90	16,518	14,487	1,267	410	354	*25.7*	*17.1*	*13.2*	*9.5*
71-80	18,691	15,307	1,943	728	713	*27.1*	*26.2*	*23.4*	*19.1*
61-70	7,974	6,001	1,030	435	508	*10.6*	*13.9*	*14.0*	*13.6*
51-60	8,583	5,907	1,301	607	768	*10.5*	*17.6*	*19.5*	*20.6*
41-50	3,173	1,959	509	265	440	*3.5*	*6.9*	*8.5*	*11.8*
31-40	2,502	1,419	414	257	412	*2.5*	*5.6*	*8.3*	*11.0*
21-30	806	382	166	83	175	*0.7*	*2.2*	*2.7*	*4.7*
11-20	561	194	111	89	167	*0.3*	*1.5*	*2.9*	*4.5*
0-10	154	46	23	29	56	*0.1*	*0.3*	*0.9*	*1.5*

* 1 = Very low risk state; 2 = Moderate Cashflow problems state; 3 = Moderate Deprivation state; 4. Very high risk of both state

** Percentages represent column proportions to provide composition of each state

A heatmap of state transition probabilities for the focal, time-homogeneous 4 state model, is detailed in Table 31. This table details the likelihood of transitioning from one latent state at time *t*, to another latent state at time *t+1*. Table 32 complements this by presenting the total number of transitions from one latent state to another across all ten waves of analysis. Several patterns are evident upon inspection of these tables.

Firstly, respondents were most likely to remain in the state they had occupied at the previous time point. Specifically, occupying the *very low risk* state at time *t* was associated with a 98.2% probability of remaining in that state at time *t+1*. Similarly, respondents in the *moderate cashflow problems* state at time *t* had an 82.9% chance of remaining in that state at time *t+1*, an 83.5% chance of remaining in the *moderate deprivation* state, and a 74.7% chance of remaining in the *very high risk of both* state between time *t* and time *t+1*.

Secondly, the very low risk state was highly stable. The probability of transitioning out of this state to the moderate cashflow problems state was 1.1%, while transitions to the moderate deprivation and very high risk of both states were both less than one percent.

In comparison, the moderate cashflow problems and moderate deprivation latent states were slightly less stable. Specifically, respondents in the moderate cashflow problems state had a greater chance of transitioning into the very low risk state (11.4%), than the very high risk of both state (5.7%). In contrast, respondents in the moderate deprivation state had a slightly lower chance of transitioning into the very low risk state (7.4%) than the very high risk of both state (9.2%). Moreover, this also highlights that the risk of transitioning into the very high risk of both state is almost twice as high when the transition is from the moderate deprivation state, compared to when the transition is from the moderate cashflow problems state. Interestingly, the chance of transitioning from the moderate cashflow problems state to the moderate deprivation state, and of transitioning from the moderate deprivation state to the moderate cashflow problem state were both highly unlikely (0.0%). Finally, respondents in the very high risk of both state had a 12.0% chance of transitioning into the moderate deprivation state and an 11.3% chance of transitioning to the moderate cashflow problems state. The chance of transitioning into the very low risk state was comparatively low (2.0%), indicating that those occupying the very high risk state have a very low chance of moving out of any form of financial hardship.

Table 31

Transition probability matrix – the probability of transitioning from one latent state to another between time *t* and time *t*+1[37]

	To State (*t*+1)			
From State (*t*)	Very Low Risk	Mod. Cashflow Problems	Mod. Deprivation	Very High Risk - Both
Very Low Risk	0.982	0.011	0.005	0.002
Mod. Cashflow Problems	0.114	0.829	0.000	0.057
Mod. Deprivation	0.074	0.000	0.835	0.092
Very High Risk - Both	0.020	0.113	0.120	0.747

[37] Colour key to assist in interpretation of transition probability values presented in Table 31. Dark blue represents a very low probability of transition from one state to another from time *t* to time *t+1*. Bright red represents a very high probability of transition from one state to another from time *t* to time *t+1*.

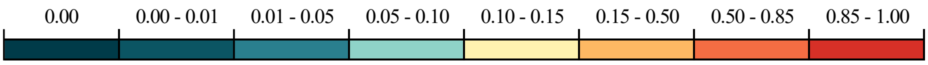

Table 32

Frequency of transitions between latent financial hardship states

Pooled across all ten waves of analysis

	To State (*t+1*)			
From State (*t*)	Very Low Risk	Mod. Cashflow Problems	Mod. Deprivation	Very High Risk - Both
Very Low Risk	49,955	142	440	64
Mod. Cashflow Problems	715	5761	29	389
Mod. Deprivation	170	8	2371	274
Very High Risk - Both	59	338	362	2535

Table 33 presents the corresponding multivariable regression coefficients and 95% confidence intervals from a series of linear mixed-effects models assessing the relationship between specific transitions from one latent state to another and mental health, adjusting for prior mental health. Table 34 presents multivariable regression coefficients and 95% confidence intervals from a linear mixed-effects model estimating the overall relationship between each latent financial hardship state and next-wave mental health.

Firstly, the relationship between transitions from the very low risk state with mental health were examined (Model 1). The vast majority of respondents occupying the very low risk state continued to occupy this state at the succeeding time point (n = 49,955). However, the next most frequent transition was from very low risk to moderate cashflow problems (n = 440) (Table 32). The multivariable analysis demonstrated that, compared to remaining in the very low risk state, mental health reduced by 2.3 points for transitions to moderate cashflow problems (95% CI = -3.3, -1.3), 3.9 points for transitions to moderate deprivation (95% CI = -5.7, -2.1), and 8.3 points for transitions to the very high risk of both state (95% CI = -11.0, -5.7). With respect to transitions from the moderate cashflow problems state (Model 2), again the majority of respondents remained in this state at the next time point (n = 5,761). The multivariable analysis illustrated that, compared to remaining in the moderate cashflow problems state, mental health reduced by 5.5 points for transitions to the very high risk of both state (95% CI = -6.9, -4.1). Conversely, transitions into the very low risk state were associated with an increase in mental health of 2 points (95% CI = 0.92, 3.0). The transition to the moderate deprivation state only occurred 29 times, hence results must be interpreted with this small sample in mind. Nonetheless, it was associated with a 5.9 point reduction in mental health (95% CI = -11.0, -0.8).

With respect to transitions from the moderate deprivation state (Model 3), again the majority of respondents remained in this state at the next time point (n = 2,371). The multivariable analysis illustrated that, compared to remaining in the moderate deprivation state, mental health reduced by 2.1 points for transitions to the very high risk of both state (95% CI = -3.9, -0.31). Conversely, transitions into the very low risk state were associated with an increase in mental health of 2.5 points (95% CI = 0.29, 4.7).

With respect to transitions from the very high risk of both state (Model 4), again the majority of respondents remained in this state at the next time point (n = 2,535). The multivariable analysis illustrated that, compared to remaining in the very high risk of both state, mental health increased by 2.8 points for transitions to the moderate deprivation state (95% CI = 1.1, 4.5), 4.4 points for transitions to the moderate cashflow problems state, (95% CI = 2.6, 6.2), 4.3 points for transitions to the very low risk state (95% CI = 0.24, 8.4).

With respect to the relationship between latent financial hardship state and next-wave mental health, a clear gradient was observed (Table 34). Compared to the very low risk state, the moderate cashflow problems state was associated with a 2.7 point lower mental health score (95% CI = -3.2, -2.3), the moderate deprivation state was associated with a 5.1 point lower mental health score (95% CI = -5.8, -4.4), and the very high risk of both state was associated with a 6.1 point lower mental health score (95% CI = -6.7, -5.4).

Table 33

Multivariate mixed-effects models with random intercept, assessing the association between latent financial hardship state transitions and mental health at time *t*, while controlling for mental health at *t*-1

Bold denotes statistical significance

Beta represents the difference in predicted SF-36 scores between each transition category and the associated reference level

	Model 1		Model 2		Model 3		Model 4	
Characteristic	**Beta**	**95% CI**	**Beta**	**95% CI**	**Beta**	**95% CI**	**Beta**	**95% CI**
Transition								
From Very Low Risk								
to Very Low Risk	—	—						
to Mod. Cashflow problems	-2.3	**-3.3, -1.3**						
to Mod. Deprivation	-3.9	**-5.7, -2.1**						
to Very High Risk - Both	-8.3	**-11, -5.7**						
From Mod. Cashflow problems								
to Very Low Risk			2	**0.92, 3.0**				
to Mod. Cashflow problems			—	—				
to Mod. Deprivation *			-5.9	**-11, -0.80**				
to Very High Risk - Both			-5.5	**-6.9, -4.1**				
From Mod. Deprivation								
to Very Low Risk					2.5	**0.29, 4.7**		
to Mod. Cashflow problems **					2.1	-7.9, 12		
to Mod. Deprivation					—	—		
to Very High Risk - Both					-2.1	**-3.9, -0.31**		
From Very High Risk - Both								
to Very Low Risk							4.3	**0.24, 8.4**
to Mod. Cashflow problems							4.4	**2.6, 6.2**
to Mod. Deprivation							2.8	**1.1, 4.5**
to Very High Risk - Both							—	—
Mental Health (Prior)								
SF-36	0.27	**0.26, 0.28**	0.37	**0.35, 0.40**	0.39	**0.35, 0.42**	0.47	**0.44, 0.50**

* The transition from Mod. Cashflow problems to Mod. Deprivation only occurred 29 times

** The transition from Mod. Deprivation to Mod. Cashflow problems only occurred 8 times

Table 34

Multivariate mixed-effects model with random intercept, assessing the association between latent financial hardship state at time *t* and mental health at time *t*+1.

Bold denotes statistical significance

Beta represents the difference in predicted SF-36 scores at time *t*+1 by LTA State at time *t*

Characteristic	Beta	95% CI
LTA State		
Very Low Risk	—	—
Mod. Cashflow problems	-2.7	**-3.2, -2.3**
Mod. Deprivation	-5.1	**-5.8, -4.4**
Very high risk - Both	-6.1	**-6.7, -5.4**

Discussion

General Findings

The previous chapter of this thesis showed that stable between-person differences explained a substantially larger proportion of the variance in the association between financial hardship and mental health than within-person differences. Building upon this finding, the present chapter aimed to explicitly model these between-person differences in financial hardship experience, to identify whether there exist distinct longitudinal profiles of financial hardship, and to assess how these profiles were associated with mental health.

The social sequence analysis highlighted that the vast majority of respondents reported either no hardship over the ten waves of analysis, or just a single wave of cashflow problems. Unsurprisingly, fit indices provided support for a two cluster solution, defined principally by the relative absence (cluster 1) or persistent presence (cluster 2) of financial hardship. A descriptive examination comparing average mental health (SF-36 MHI-5) across the two clusters revealed substantial differences, ranging from roughly 15 to 18 points over the ten years between 2014 and 2023.

The analysis using latent Markov modelling identified four latent financial hardship states defined according to the probability of experiencing cashflow problems and deprivation. Specifically, this included a state defined by a very low risk of experiencing either hardship subdimension (*very low risk*), a state defined by a moderate probability of experiencing cashflow problems (*moderate cashflow problems*), a state defined by a moderate probability of experiencing deprivation (*moderate deprivation*), and a final state defined by a very high probability of experiencing both cashflow problems and deprivation (*very high risk of both*). Given these probabilities, the four latent states can be understood as following an ordered gradient of increasingly severe financial hardship. Specifically, the least severe degree of financial hardship is reflected in the *very low risk* state, followed by the *moderate cashflow problems* state, the *moderate deprivation* state, and finally the *very high risk of both* state. This ordering is informed by work by Bray (2001), who suggested that cashflow problems reflect circumstances where a household may attempt to manage limited financial resources by delaying bill payments, or seeking monetary assistance from friends or family. Conversely, deprivation represents a far more precarious financial position in which a household cannot afford the basic necessities accepted as a minimum standard of living in society. Understanding the four states through this ordering has several implications. Firstly, the vast majority of the sample (approximately 75% to 80%) occupied the very low risk state at all ten waves of analysis, whereas a much smaller proportion occupied the three remaining states. This aligns with the prevalence estimates reported in the first analytic chapter, which demonstrated that approximately 78% to 82% of people did not experience financial hardship.

Secondly, state stability across time points was a defining characteristic of this analysis. Overwhelmingly, respondents were most likely to occupy the same latent financial hardship state they occupied in the year prior. This was especially true for the *very low risk* state, where transitions into higher risk financial hardship states were highly unlikely. Put simply, it was highly uncommon for people to transition out of the lowest risk latent financial hardship state. Thirdly, where latent state transitions were observed, downward transitions into lower risk states (n = 1,652) were more numerous than upward transitions into higher risk states (n = 1,338). This suggests that the sample, overall, demonstrated a slight reduction in financial hardship risk. In this, a parallel could be observed between the latent transition analysis and the social sequence analysis. Namely, the observed state stability reflected the broad finding from the social sequence analysis that people generally fell into two categories of financial hardship experience – relative absence of hardship, or relatively persistent hardship experience.

Moreover, the probability of specific transitions revealed interesting information about how people move between the varying latent financial hardship states. Specifically, respondents in the *moderate cashflow problems* state had a greater chance of moving to a lower risk latent financial hardship state, than a higher risk state. In comparison, respondents in the *moderate deprivation* state had a greater chance of moving to a higher risk latent financial hardship state, than a lower risk state. Moreover, when respondents did transition to a higher risk latent state from the *moderate cashflow problems* state, they were more likely to transition to the *very high risk of both* state than the *moderate deprivation* state. In other words, people were more likely to transition into experiencing both cashflow problems and deprivation, rather than just deprivation. This result should also be understood in concert with the analogous transition from the *moderate deprivation* state. Specifically, the chance of transitioning to the *very high risk of both* state was 5.7% from the *moderate cashflow problems* state, while the chance of transitioning to the *very high risk of both* state was 9.2% from the *moderate deprivation* state. Taken together, this suggests that the risk of transitioning into the *very high risk of both* state (i.e., the highest financial hardship risk state) is almost twice as high when one is in the *moderate deprivation* state compared to the *moderate cashflow problems* state.

Finally, the majority of latent state transitions were associated with significant changes in mental health. Specifically, transitions from a lower risk latent financial hardship state to a higher risk state were robustly associated with a deleterious impact to mental health, while transitions from a higher risk latent financial hardship state to a lower risk state were consistently associated with improvements to mental health. Moreover, the magnitude of these deteriorations and improvements to mental health varied according to the change in overall financial hardship severity associated with the specific latent state transition. For example, a transition from the *very low risk* state to the *very high risk of both* state was substantially worse for mental health than a transition from the *very low risk* state to the *moderate cashflow problems* state. In comparison, transitions from the *very high risk of both* state to the *very low risk* state were associated with a greater improvement to mental health than a transition from the *very high risk of both state* to the *moderate deprivation* state.

Relationship to Previous Work

These findings align with prior research using latent transition analysis and latent Markov modelling to examine both general and mental health outcomes as a function of stability or transition into varying states of socioeconomic disadvantage. For example, analysis of 17,216 children across five waves of the UK Millennium Cohort Study found that exposure to socioeconomic disadvantage between the ages of 3 and 14 significantly increased the likelihood of transitioning into moderate or high emotional and behavioural symptom profiles (Picoito et al., 2021). Similarly, a two-wave analysis of young adults from Hong Kong showed that changes in financial hardship were significantly associated with a higher likelihood of transitioning from a low to high psychological distress state (Li et al., 2025). Another study that used latent transition analysis showed that individuals in a stable poor-health state experienced the highest levels of socioeconomic disadvantage (defined in terms of employment status, occupation type, and household income). In contrast, individuals in stable good-health state experienced the highest levels of socioeconomic advantage (Sacker et al., 2007).

Strengths and Limitations

The analysis presented within this chapter has several key strengths. Firstly, it made use of data from the HILDA survey. As noted previously, the HILDA survey is a very high quality, nationally representative longitudinal panel, that has collected annual sociodemographic, income, wealth, and health information about the Australian population since 2001. The sample used in this study comprised 7,068 unique individuals, who contributed a total of 70,680 observations over 10 waves between 2014 and 2023. Re-interview rates have consistently exceeded 93%, which has provided repeated assessment of financial hardship and mental health information from a sizeable majority of panel members. In turn, this has enabled an examination of the longitudinal profiles of financial hardship experience characterising the Australian population from 2014 to 2023, and the modelling of how people move between varying states of financial hardship. Moreover, the measures used to assess financial hardship and mental health have demonstrated reliability and validity. The measure of financial hardship has found widespread use within research examining socioeconomic disadvantage in Australia for more than two decades (Bray, 2001; Butterworth et al., 2012; Butterworth & Crosier, 2005; Crowe et al., 2016; Kiely et al., 2015). Similarly, the MHI-5 from the broader SF-36 has provided robust and reliable estimates of mental health in countless studies. A further strength of this chapter lies in the use of latent transition analysis. Unlike latent class analysis and group-based trajectory modelling, which take a static approach to class membership, latent transition analysis provides detailed insight into how people move between latent states over time. Furthermore, to the best of the author's knowledge, this is the first study to apply LTA to the identification of latent financial hardship states and the examination of how people transition between them. Finally, along with LTA, this study made complementary use of SSA and mixed-effects regression modelling. Multiple analytic approaches were utilised to provide a comprehensive examination of between-person differences in financial hardship experience over time, and to understand how these differences are linked to poor mental health. Collectively, these varying approaches triangulate, providing a cohesive understanding of the focal relationship.

Some limitations to this study must also be noted. This study used just ten of the (currently) available 23 waves of HILDA survey data. Additionally, the analytic sample only comprised participants with complete financial hardship and mental health data within these ten waves. These decisions served a twofold purpose. Firstly, a key aim of this analysis was to describe and visualise the most common ways in which people experience financial hardship over time. However, the optimal matching algorithms used in social sequence analysis can be sensitive to missing values. In other words, clustering solutions can be defined by sample missingness, instead of elucidating broader trends attendant to the focal variable(s).

Restricting our sample to complete cases overcame this. Nonetheless, research using identical methodology that *included* missing values would also be instructive, insofar as illuminating patterns of attrition related to financial hardship and mental health. Secondly, restricting the sample to ten waves ensured that a sample large enough to ensure robust conclusions was maintained. Each additional wave of data reduced the chance of a respondent having complete case information. Thus, ten waves struck a balance between maximising sample size, and providing a time period of adequate duration to draw long-term inferences. However, it is possible that these decisions may have biased the resultant analytic sample. As detailed in Appendix D.1, the analysed sample was slightly more socioeconomically advantaged and healthier than the broader baseline sample. This is consistent with research that has shown elevated rates of attrition amongst those reporting lower socioeconomic status and poorer health within the HILDA survey and related international panel studies (Baigrie & Eyal, 2014; Lipps, 2009; Lugtig, 2014; Watson & Wooden, 2009; Wooden & Watson, 2004). As a result, the findings within this chapter may be less generalisable to those experiencing both poorer physical and mental health, and greater financial hardship. This may have also resulted in a smaller proportion of respondents represented in the three latent states reflecting varying financial hardship experience, and reduced the strength of the observed associations between both latent state membership and latent state transitions, with mental health. On the note of sample size and selection characteristics, it is worth reinforcing that the sample in this analysis was not weighted to align with annual Australian population benchmarks. Thus, generalisations about the Australian population cannot be made.

Another limitation concerns the use of different variables in the social sequence analysis and latent transition analysis. The social sequence analysis employed a single, four-level variable that distinguished between no hardship, cashflow problems, deprivation, and both cashflow problems and deprivation. However, the latent transition analysis utilised two ‘yes/no’ binary variables that categorised whether respondents had experienced cashflow problems, or deprivation. Given this, comparisons between the clusters and states derived from the SSA and LTA (respectively) are inexact. To improve comparability, future research could employ multi-channel sequence analysis using the two binary indicators of cashflow problems and deprivation. However, the complexity of this approach placed it beyond the scope of the present chapter.

Finally, as per any cluster-based approach that groups respondents into discrete classes, state assignment in LTA can be ambiguous in instances where a respondent has similar or equal posterior probabilities. However, this limitation can be overcome by carefully considering fit indices, and the substantive meaning of resultant clusters to ensure the optimal class solution is selected.

Future Research

The findings presented here provide a foundation for answering a series of concrete follow-up questions. Firstly, future research could assess the degree to which additional sociodemographic factors, such as sex, age, birth cohort, education, employment status, income, area-level disadvantage, or physical health predict both latent state membership and transitions between latent financial hardship states. Modelling the effect of time-invariant and time-varying factors on transitions would provide insight into who is more likely to recover from financial hardship, who is more likely to move towards increasingly severe states of financial hardship, and who is more likely to remain in the state of hardship they currently occupy. Put simply, such work would assist in identifying who is at risk now, and who may be at risk in the future.

Another meaningful extension of the LTA presented here, would be to estimate a multiple-process latent transition model (Sacker et al., 2013). This approach allows researchers to examine how state transitions in one process influence state transitions within another over time. With respect to this research, it could be used to model the dynamic interaction between transitions of both financial hardship and mental health, and explore moderating effects of each state on recovery, worsening or maintenance trajectories. For example, Sacker and colleagues (2013) used a multiple-process latent transition model with data from the British Household Panel Survey (BHPS) to examine the longitudinal relationship between poverty and health. They demonstrated that the directional pathway from health to poverty was *mediated* by non-employment, whereas the directional pathway from poverty to health was *confounded* by non-employment.

There also exist several possibilities to extend and enrich the findings derived from the SSA. The SSA conducted in this study grouped the whole sample together. This had the effect of averaging financial hardship profiles across all respondents. However, SSA is often used to track people of the same age over a defined period of time and observe whether distinct profiles (with respect to the variables under study) emerge over the life-course. In light of the findings detailed within the second analytic chapter of this thesis – specifically that the prevalence of financial hardship was highest amongst young adults, coinciding with the time that many would make the transition out of the family home and into tertiary study and initial employment – it would be germane to observe whether the experience of financial hardship at this age sets in motion different long-term trajectories of hardship and/or mental health. Such an analysis could be extended further using a mature dataset like HILDA, by comparing birth cohorts to assess whether profiles of hardship experience have changed over time. Similarly, further analyses should also attempt to discern whether long-term profiles of hardship differ by sex.

Conclusion

This chapter provides substantial evidence of distinct between-person differences in financial hardship experience over the last ten years in Australia, and significant variation in mental health across these differences.

Using social sequence analysis, two distinct clusters of financial hardship experience were identified. The first cluster was defined by the relative absence of financial hardship, while the second cluster was defined by the persistent experience of either cashflow problems, deprivation, or both cashflow problems and deprivation. This finding aligns with earlier descriptive analysis of the long-term prevalence of financial hardship in Australia, which showed that a substantial majority of the population did not experience hardship in any given year (ranging from ≈ 70% to 80% between 2001 and 2023), while a sizable minority did (≈ 20% - 30%). Descriptive comparison of the wave-on-wave average mental health of these two clusters revealed sizeable differences. These findings suggest two key points; (1) There exists a substantial and persistent social bifurcation between the life-courses of those who experience financial hardship, and those who do not; and (2) that mental health (perhaps unsurprisingly), is much worse amongst those whose longitudinal profile is punctuated by persistent financial hardship.

Additionally, the latent transition analysis revealed four, highly stable latent financial hardship states, defined by the probability of experiencing cashflow problems, deprivation, or both of these subdimensions concurrently. These four states differed in the severity of financial hardship they represented, forming an ordered hierarchy with respect to financial hardship risk. This analysis complemented the broader descriptive findings of the social sequence analysis in several ways. Firstly, it yielded insight into how people transition between varying states of financial hardship over time. Notably, states were characterised by substantial stability, indicating that people overwhelmingly tended to remain in the same financial hardship state over time. This finding has contrasting implications. Principally, individuals who are not experiencing financial hardship are highly unlikely to do so in the future. However, individuals who are currently experiencing financial hardship are also highly unlikely to transcend it. Secondly, membership within each of these states was associated with significant differences in mental health. Membership in lower risk latent financial hardship states was associated with significantly better mental health, while membership in higher risk states was associated with significantly poorer mental health. This finding corresponds to an effect of cumulative financial hardship risk, evidenced by the distinct social gradient mental health followed across the four latent states.

Finally, movement between latent states was associated with significant deterioration or improvement to mental health, in proportion to the change in financial hardship severity associated with each specific transition. Put simply, transitions into higher risk latent states were associated with declines in mental health, while transitions into lower risk states were associated with mental health improvements. Collectively, this highlights that changes in the experience of financial hardship are associated with within-person changes in mental health. In turn, this points towards financial hardship sharing more than just a correlational association with mental health and provides evidence suggesting that financial hardship may play a key role in generating and/or maintaining the observed gradient in mental health. This pattern of results is consistent with social causation, without demonstrating causation per se. Overall, this indicates that both one’s level of financial hardship, and changes in financial hardship severity, are associated with mental health.

Chapter 6 – General Discussion

Background

Mental disorders are one of the leading contributors to global burden of disease, disability and excess mortality (Charlson et al., 2015; Fan et al., 2025; GBD Mental Disorders Collaborators, 2022; Murray et al., 2015; Rehm & Shield, 2019; Vigo et al., 2016; Vos et al., 2015, 2017; Whiteford et al., 2013). This is also true for Australia. Consistent epidemiological surveillance since the mid 1990's has demonstrated mental disorders to be common and contribute significantly to national burden of disease. Concerningly, this work has also evidenced stable, and even increasing, prevalence of mental disorders across the Australian population over the past thirty years (AIHW, 2023; Butterworth et al., 2020; Enticott et al., 2022; Slade et al., 2024). This trend is despite increased funding to the mental health sector, vast expansion of treatment services, and evidence of considerable uptake in service use (AIHW, 2023; Harvey et al., 2017; Jorm, 2014; Pirkis et al., 2011; Whiteford et al., 2014). However, Australia is not unique in demonstrating a disconnect between expanded treatment and stable or increasing prevalence of mental disorders – this pattern is evident across many other high-income developed countries (Furukawa & Kessler, 2019; Jorm, 2014; Jorm et al., 2017; Jorm, 2018; Meadows et al., 2019; Mulder et al., 2017; Ormel et al., 2019, 2022; Ormel & Emmelkamp, 2023). The body of work presented within this thesis proceeds, and gathers urgency from, this apparent paradox. In essence, the fundamental question is: *what may account for the persistent prevalence of mental disorders and associated burden of disease, observed over the past thirty years?* Given this, action upon a broader set of modifiable factors is proposed. For example, despite an abundance of evidence demonstrating the link between socioeconomic disadvantage and mental illness (Kirkbride et al., 2024), integration of this work into prevention efforts remains limited. In turn, the conditions associated with socioeconomic disadvantage and mental disorder remain under-addressed and persistent for a sizeable proportion of the Australian population. The overarching aim of this thesis is to inform prevention by quantifying the association between financial hardship and mental health using longitudinal data and longitudinal analytic techniques.

Overview of Studies

The primary focus of this thesis was on characterising the experience of financial hardship in the Australian population and extending our understanding of how it is associated with mental health. This was distilled into a series of key research questions that were investigated through a systematic review and three empirical studies.

Specifically, the systematic review aimed to appraise and synthesise prevailing international evidence that has assessed the relationship between financial hardship and mental health using longitudinal data and longitudinal analytic techniques. This chapter sought to answer the broad questions of: (1.1) What is the overall relationship between financial hardship and mental health? (1.2) What constructs and terms have been used to define and measure financial hardship? And (1.3) To what extent can this relationship be explained by heterogeneity in methodological, analytic, or participant characteristics? Building upon this foundation, while narrowing the focus to the Australian context, the three ensuing empirical studies used data from the nationally representative HILDA survey to answer the questions: (2.1) What is the overall prevalence of financial hardship in Australia from 2001 to 2023? (2.2) What are the key sociodemographic correlates of financial hardship in Australia? (2.3) How has the strength of the relationship between sex, and age with financial hardship changed over time? (3.1) What is the temporal ordering between financial hardship and mental health? (3.2) What is the strength of the within-person effects for each of the *social causation* and *health selection* directional pathways operating between financial hardship and mental health? (3.3) What is the relative strength of the within- and between-person components of the relationship between financial hardship and mental health? (4.1) To what extent do distinct profiles of financial hardship experience exist? (4.2) To what extent do distinct latent financial hardship states exist? (4.3) What is the relationship between these latent financial hardship states and mental health? (4.4) What is the relationship between transitioning from one latent financial hardship state to another with mental health?

Overview of Findings

The principal finding from this body of work was the strength and consistency of the relationship between financial hardship and mental health. This result was confirmed across a large sample of international research, along with primary analysis of nationally representative data from Australia. In both instances, the observed association was highly robust – firstly across studies differing in setting, sample, methodology, and analytic approach, and secondly, in multivariate analyses that controlled for an array of demographic and socioeconomic factors. Financial hardship was also found to affect a sizeable proportion of the Australian population – ranging from approximately 30% in 2001 to approximately 20% in 2023. Building upon this, analyses also highlighted a substantial bifurcation between people with respect to financial hardship experience – specifically between those who rarely, if ever, experienced financial hardship, and those who experienced relatively persistent financial hardship. The mental health of those who experienced persistent financial hardship was substantially worse than those who never, or only rarely, experienced financial hardship. Additional analyses also demonstrated that transitions into higher risk financial hardship states to be associated with declines in mental health, and transitions into lower risk financial hardship states to be associated with mental health improvements. Specific findings in relation to each of the aforementioned key research questions are presented below.

Specific Findings

What is the Overall Longitudinal Relationship between Financial Hardship and Mental Health?

The systematic review demonstrated an overwhelmingly positive longitudinal association between financial hardship experience and poorer mental health. Specifically, across 94 studies, 87.1% of analyses assessing the relationship between financial hardship and mental health using a multivariate (adjusted) approach found a significant longitudinal association. As noted above, this association was highly robust, generalising across study locations, study designs, sample characteristics, confounders and various measures of mental health and financial hardship. In addition, the measures used to evaluate financial hardship were highly diverse. These varied with respect to implementation (multi-item scale, general question about finances, single item), the domains of hardship assessed, and whether the focus was on perceived or actual deprivation. As a result, the range of measures were highly idiosyncratic – a finding which reflects the absence of a universal measure of financial hardship.

What is the Prevalence of Financial Hardship in Australia? What are the Correlates?

The prevalence of financial hardship in Australia has declined from approximately 30% in 2001 to approximately 20% in 2023. Additional analyses of trends in the two subdimensions of financial hardship – cashflow problems and deprivation – revealed a pattern of divergence over time. Overall, the prevalence of cashflow problems declined from approximately 26% to 18% between 2001 and 2023, whereas the prevalence of deprivation remained between 12% and 13% over the same period. Notably, increases in deprivation were observed amongst females and adolescents aged 15-19 years old. Since 2022, the prevalence of all three measures has demonstrated a particularly sharp increase. With respect to the individual items comprising these measures, not being able to pay electricity, gas, or telephone bills on time, and asking for financial help from friends or family were the most prevalent forms of hardship. Moreover, the prevalence of all three measures showed sensitivity to macro-economic shocks – namely, the GFC in 2008, COVID in 2020, and increases to CPI inflation and the Reserve Bank of Australia Cash Rate in 2023. Each of these events coincided with a marked rise in the prevalence of financial hardship, cashflow problems, and deprivation.

Lower socioeconomic groups consistently evidenced both higher rates and significantly elevated odds of experiencing both forms of hardship. For example, those reporting lower household income, holding lower educational qualifications, residing in areas of greater disadvantage, and of poorer physical health all demonstrated higher rates and greater odds of cashflow problems and deprivation. This was also true for females, people aged 20-29 years old, and those born between 1970 and 1989. However, the highest odds of experiencing both cashflow problems and deprivation were observed amongst individuals reporting very poor mental health. The magnitude of this relationship was particularly striking. Compared to individuals in the highest decile, those in the lowest decile of mental health were greater than six times more likely to experience cashflow problems, and greater than thirteen times more likely to experience deprivation.

What is the Temporal Ordering and Strength of the Bi-directional Relationship Between Financial Hardship and Mental Health?

A consistent negative concurrent association was observed between financial hardship and mental health, indicating that greater financial hardship was associated with poorer mental health (and vice-versa) at the same time point. However, the temporal ordering between financial hardship and mental health remains unclear. This is possibly due to two related methodological factors: (1) the focal measures of financial hardship and mental health being assessed over different timeframes (past twelve months for financial hardship and past four weeks for mental health); and (2) the twelve-month interval between waves possibly being too long to observe temporally ordered effects. Similarly, the strength of the *social causation* and *health selection* directional effects was inconsistent and therefore also remains unclear. Given this, the weight of evidence suggests that the relationship between financial hardship and mental health is primarily concurrent. However, these analyses did highlight that the predominant share of variation in the financial hardship to mental health association is attributable to stable trait-level differences between individuals, as opposed to within-person variation over time. In other words, the observed association between these factors is largely driven by persistent structural differences *between* people, as opposed to temporary variations in hardship or mental health that individuals may experience over time. In short, this suggests that the same people who tend to experience greater financial hardship, also tend to have poorer mental health.

Do Distinct Profiles of Hardship Exist? Do Transitions between Latent Hardship States Impact Mental Health?

Building upon the previous study which highlighted striking between-person differences in the focal relationship, two distinct profiles of financial hardship experience were identified. These comprised a very large group of people who rarely, if ever, experienced financial hardship, and a much smaller group composed of people who reported experiencing relatively persistent financial hardship. Further analysis identified four distinct latent financial hardship states. This included a state defined by 'very low risk' of financial hardship, states defined by 'moderate cashflow problems' and 'moderate deprivation', and a final state defined by a 'very high risk' of experiencing *both* cashflow problems and deprivation. Each of these states were characterised by considerable stability. This means that individuals are overwhelmingly likely to remain in the same financial hardship state over time. Thus, those who are at low risk of experiencing financial hardship now are also unlikely to experience financial hardship in the future. Concerningly however, this finding also means that individuals who are currently experiencing financial hardship are highly likely to continue doing so into the future. A clear gradient in the risk of poor mental health was observed from the very low risk to the very high-risk state. Additionally, transitions from a lower financial hardship risk state to a higher financial hardship risk state were associated with declines in mental health, while transitions to states characterising lower hardship risk were associated with mental health improvement.

Interpretation

The systematic review overwhelmingly confirmed findings from individual studies that have reported a very strong association between financial hardship (or similar outcome-based measures of material deprivation) and mental health (Butterworth et al., 2009; Butterworth et al., 2012; Crowe et al., 2016; Foulds et al., 2014; Kiely et al., 2015). Additionally, this review clearly demonstrated that the link between financial hardship and mental health is independent of time, place, sample, methodology, and analytic approach. Moreover, these findings conform to an array of similar systematic reviews and meta-analyses conducted over the past three decades, evidencing a significant relationship between related measures of socioeconomic disadvantage and mental health. At least 25 review papers have summarised the influence of a diverse range of socioeconomic factors on mental health, using various populations, and spanning individual, neighbourhood, and macro levels of analysis. The vast majority have found consistent evidence linking socioeconomic disadvantage to poorer mental health. Specifically, reviews have linked poorer mental health to absolute and relative poverty, unemployment, income, debt, housing disadvantage, socioeconomic status, socioeconomic position, income inequality and area-level disadvantage (Feinstein, 1993; Fitch et al., 2011; Fryers et al., 2003; Iemmi et al., 2016; Lorant, 2003; Lund et al., 2010; Muntaner et al., 2004; Patel et al., 2018; Paul & Moser, 2009; Ribeiro et al., 2017; R. Richardson et al., 2015; Singh et al., 2019; Thomson et al., 2023; Turunen & Hiilamo, 2014). Taken together, the systematic review underscores the inextricable link between the fundamental material circumstances characterising an individual's life and their mental health. Individuals who cannot afford basic necessities – such as clothing, medicines, food, housing, or utilities – demonstrate significantly poorer mental health than those who can.

This fundamental finding was replicated throughout the entirety of this thesis. Given the strength and consistency of the link between financial hardship experience and poor mental health, it was crucial to quantify the proportion of people exposed, and how this has changed over time. Accordingly, an examination of the prevalence of financial hardship in Australia between 2001 and 2023 was conducted. While the overall prevalence of financial hardship has declined between these two time points, rates of financial hardship were markedly higher than rates of income poverty (measured using the 50% median income threshold). In other words, rates of socioeconomic disadvantage were substantially higher when measured against the proportion of the population going without basic necessities, than the proportion of the population meeting criteria for income poverty. There are several explanations for this.

Firstly, the asymmetry between outcome-based assessment of socioeconomic disadvantage and income has been demonstrated in a range of empirical analyses (Berthoud & Bryan, 2011; Foulds et al., 2014; Lorant et al., 2007; Whelan et al., 2001). While not perfectly aligned, measures of *persistent* income poverty over a sustained period provide a better fit to outcome-based measurement of socioeconomic disadvantage than point assessments of annual household income (Nolan & Whelan, 2011). Secondly, the proportion of people meeting criteria for socioeconomic disadvantage when evaluated against an outcome-based measure varies depending on the number of items in the scale a respondent is required to affirm. The threshold for financial hardship defined throughout this thesis was highly sensitive, requiring respondents to affirm just one item of the seven-item scale. The implication being that people who experience a temporary or ‘one-off’ financial shock will meet this definition of hardship. By comparison, a stricter threshold for defining hardship has been used by the Australian Institute of Health and Welfare (AIHW). Specifically, the AIHW used a measure of ‘severe financial stress’ which was defined by the experience of at least one of the following: (1) Not being able to pay bills; (2) Not being able to pay the mortgage or rent on time; or (3) Going without meals. Using this threshold, the AIHW estimated that severe financial stress has declined from approximately 20% in 2001 to 14% in 2023 (Australian Institute of Health and Welfare, 2025a). These figures align more closely with estimates of relative income poverty in Australia over a similar period. Specifically, analyses have estimated a slight rise in income poverty (assessed using the 50% median income threshold) from 12.4% to 13.3% between 2001 and 2022 (Bray, 2024). Similarly, outcome-based measures are also sensitive to the items of deprivation they assess. For example, the seven-item scale used throughout this body of work did not assess whether respondents had gone without medicines, doctor’s appointments, or other essential healthcare needs due to a shortage of money. However, the inclusion or exclusion of such an item will identify different people as experiencing hardship in different countries – particularly with respect to variations in the provision of publicly funded healthcare.

Another source of disagreement between income poverty assessment and outcome-based measurement of disadvantage is the common misreporting of income in household panel surveys – particularly income derived from self-employment, capital assets, or imputed property rents (Nolan & Whelan, 2011). Moreover, households with the same income can report significantly different experiences when assessing socioeconomic disadvantage in terms of outcomes. This can be due to differences in a household’s wealth assets and private savings, or variations in the amount of debt held. For example, households deriving an income from wealth holdings, or with adequate monetary savings, can smooth out periods of low income and avoid experiencing hardship. Conversely, households carrying substantial debt are more susceptible to experiencing hardship even whilst drawing an income above defined income poverty thresholds (Berthoud & Bryan, 2011). Similarly, substantial fixed costs attributable to housing, health insurance, debt repayments, or one-off expenses can lead to hardship in instances where income is nominally above poverty thresholds. Related to this, substantial variation in the cost of basic essentials by location, or differences between individuals in terms of chosen lifestyle and need can also lead to a separation between income- and outcome-based measurement of socioeconomic disadvantage. Individuals also vary in the extent to which they can call upon financial support from family or friends during periods of low income – resulting in those without access to external financial support being more likely to report hardship, compared to those who can.

Finally, the difference between the prevalence of financial hardship reported in this thesis, and rates of income poverty reported in related research (Bray, 2024; Saunders et al., 2022a) may indicate a decoupling that has occurred between living standards in Australia and traditional income-based measures of socioeconomic disadvantage. Specifically, income poverty thresholds shift according to the distribution of national income. However, the dramatic rise in housing costs since the early 2000's, persistent CPI inflation post-COVID, and increases to the RBA cash rate, have contributed to a substantial increase in the price of essential goods and services. The net result is that income poverty measures may be underestimating the full extent of socioeconomic disadvantage in Australia.

Broadly speaking, financial hardship was most prevalent amongst socioeconomically disadvantaged and psychologically vulnerable Australians. This finding aligns with prevailing research expanded upon in the introduction of this thesis that has consistently identified poor mental health to be associated with various measures of socioeconomic disadvantage (Allen et al., 2014; Compton & Shim, 2015; Huggard et al., 2023; Kirkbride et al., 2024; Silva et al., 2016). Several theoretical frameworks that aim to account for the observed social gradient in health outcomes are applicable to the strong association between financial hardship and mental health identified in this thesis. Financial hardship, by definition, reflects an *absence or inability to obtain basic, socially perceived necessities* due to inadequate financial resources (Mack & Lansley, 1985).

Materialist explanations stress the significance of these basic necessities, highlighting how health outcomes are directly shaped by the material conditions that characterise our lives (Lynch et al., 1997; Marmot et al., 2010). Insufficient financial resources may lead to sustained periods of lower living standards and reduced access to protective factors such as safe housing, nutritious food, and effective healthcare, which collectively undermines mental health (Pearlin, 1989; Pearlin et al., 2005).

Similarly, this finding is consistent with Fundamental Cause Theory (FCT) which posits that poverty and material deprivation are “fundamental causes” of health disparities (Link & Phelan, 1995). Specifically, poverty and material deprivation act as fundamental determinants of health inequalities by shaping access to crucial, flexible resources – such as income, knowledge, prestige, and beneficial social connections – which can be used to mitigate exposure to mental health related stressors like financial hardship, and in turn, protect against illness (Phelan et al., 2010).

Psychosocial approaches highlight that, beyond the direct impacts to health associated with poorer material living standards, experiencing disadvantage involves subjective feelings of low status, insecurity, isolation, lack of control, and shame, which act as psychological stressors (Marmot & Wilkinson, 2001, 2005). Moreover, beyond the material impact of financial shocks, people living in poverty endure substantial worry, uncertainty, and stress associated with anticipating and bearing periods of financial insecurity and deprivation – to which sustained exposure is likely to be a significant risk factor for poor mental health (Staufenbiel et al., 2013). Indeed, research by Crowe and colleagues (2016) has linked unemployment and underemployment to poorer mental health, via increased hardship and a reduced sense of control.

Additionally, mechanisms involving biological pathways have also been proposed to explain the link between chronic exposure to social and environmental stressors, and increased risk of poor mental health. For example, allostatic load is a construct that represents the cumulative “wear and tear” on multiple physiological systems – such as the hypothalamic-pituitary-adrenal axis (HPA axis), the sympathetic nervous system, the immune/inflammatory system, and the cardiovascular and metabolic systems – resulting from repeated activation in response to chronic stress (Braveman & Gottlieb, 2014; Guidi et al., 2021). Indeed, in controlled animal experiments where diet and environment have been held constant, low social status (in terms of dominance rank) has been causally associated with chronic arousal of the HPA axis, with hypercortisolism, insulin resistance, adverse cholesterol ratios, and atherosclerosis (Morgan et al., 2002; Sapolsky, 2005; Sapolsky, 1989). Importantly, this explanation dovetails with materialist and psychosocial explanations of health gradients by providing a pathway through which repeated stress activation takes a cumulative physiological toll.

Finally, cultural-behavioural models have argued that inequalities in health outcomes may be a function of variations in health-related behaviour (such as smoking rates, physical activity, alcohol use, drug consumption, and diet) between members of different socioeconomic classes (Macintyre, 1997; Øversveen et al., 2017; Pampel et al., 2010). The strong association between physical and mental health has been well documented (Behan et al., 2015; Ohrnberger et al., 2017; Sowers et al., 2009). Therefore, behaviours that compromise physical health are highly likely to undermine mental health and generate inequities in mental health outcomes across varying socioeconomic strata.

Given that socioeconomic disadvantage is a multifaceted construct, it is possible that these frameworks are complimentary and operate to varying extents across the life course. Moreover, each of them may provide unique insight into the varying pathways through which financial hardship impacts mental health. A life course approach to studying health outcomes can bring together these differing frameworks. Implicit to this approach is the recognition that socioeconomic disadvantage may accumulate over long periods of time, shaping physiological, psychosocial, behavioural, and epigenetic characteristics, along with the day-to-day conditions to which an individual is exposed (Allen et al., 2014). Consequently, the accumulation of varying degrees of advantage and disadvantage over time may contribute to substantial differences in mental health. Indeed, the evidence presented within this thesis is consistent with financial hardship being understood as a chronic stressor which degrades mental health via its association with direct material deprivation and low social status.

The temporality and directionality of the bidirectional pathways operating between financial hardship and mental health were explored. Broadly speaking, it remains unclear across existing literature examining social determinants of health whether poor socioeconomic conditions predispose people to poorer health, whether poorer health is predictive of greater socioeconomic disadvantage, whether both directions operate simultaneously, or whether each of these directional pathways are mediated by additional factors (Hudson, 2005; Perry, 1996; Warren, 2009). For example, 'social causation' theories emphasise the negative impact of low resources or socioeconomic status on health outcomes (Goldman, 1994). Theories of 'health selection' on the other hand, underscore how health problems may lead to downward social mobility (Mackenbach, 2012; Øversveen et al., 2017). Unfortunately, the results of this analysis reflected the prevailing inconsistency that has characterised prior research (Prati, 2024). Clear evidence in support of social causation or health selection effects was not found. However, a consistent negative *concurrent* within-person association was demonstrated between financial hardship and mental health, which is consistent with prior research (Butterworth et al., 2009; Butterworth et al., 2012; Kiely et al., 2015; Witteveen & Velthorst, 2020). Taken together, this suggests at least three possibilities: (1) That the relationship between financial hardship and mental health is relatively immediate; (2) That 'life shocks' are characterised by the co-occurrence of financial hardship and poor mental health; or (3) That the 12 month time interval between waves of data was too long to observe any temporal effects. Despite this, a very strong between-person effect was found. In other words, the relationship between financial hardship and mental health was demonstrated to be primarily driven by stable, trait-level differences *between* individuals, as opposed to intra-individual (or within-person) fluctuations in financial hardship experience and mental health across time. In very simple terms, the differences between people in terms of financial hardship experience and mental health were substantially greater than the differences people experienced on these factors within themselves over time. This finding was also consistent with prior work that has used the same RI-CLPM approach (Cao et al., 2021; O'Donnell et al., 2020; Prati, 2024; Su et al., 2021; Yanez et al., 2024).

Given the substantial between-person effects identified in the third empirical chapter, it was deemed expedient to explore these differences with respect to long-term financial hardship experience. This work resulted in the identification of discreet long-term hardship profiles, consisting of a large group of people who rarely experienced financial hardship, and a smaller group who experienced regular or persistent financial hardship over the assessed ten-year period. Related research has identified similar hardship trajectories (Willson & Shuey, 2016). Descriptive analysis of mental health difference between those occupying each of these profiles revealed substantial differences. Specifically, the group characterised by persistent financial hardship showed markedly lower mental health than the group who rarely experienced hardship. This analysis was extended to examine whether transitions between latent financial hardship states were associated with changes in mental health. Firstly, a set of four latent financial hardship states were identified. Collectively, it was apparent that these four states followed a gradient of increasing hardship risk. Moreover, mental health outcomes linked to transitions between these states, mirrored the underlying change in hardship risk. Put simply, transitions into higher risk financial hardship states were associated with declines in mental health, while transitions into lower risk financial hardship states were associated with improvements in mental health. It was also demonstrated that state membership was highly stable. The consequence of this being that people in a state characterised by a low risk of hardship were highly unlikely to experience hardship in the future. However, those in a state characterised by a high risk of hardship were highly likely to remain in this state going forward. Collectively, these findings align. Specifically, the predominance of between-person effects linking financial hardship and mental health was clarified by the observation that people tend to fall into two distinct hardship profiles – persistence or absence. The stability of latent hardship state membership provided further support for this interpretation.

The finding that latent state membership was highly stable is consistent with work that has cautioned against reduced social mobility due to possible links with increasing economic inequality (Corak, 2013). Indeed, evidence from Australia has indicated that both income and wealth inequality has increased (Kaplan et al., 2018; Rebechi & Rohde, 2023; Saunders, 2017; Saunders et al., 2016, 2022a). Similarly, novel multidimensional measures of inequality that include health and educational outcomes follow the same increasing trend (Rebechi & Rohde, 2023; Rohde & Guest, 2018). Together with the observed state stability, the implication is that transcending hardship in Australia may be becoming increasingly difficult.

The downstream consequences of these trends for population mental health are concerning. Particularly given the bifurcation observed throughout this thesis between those who experience hardship and poorer mental health, and those who rarely, if ever experience hardship. The implication being that it may be more difficult for individuals experiencing poor mental health to recover, if getting out of financial hardship has also become a greater challenge. This is noteworthy given that Australia is a high-income developed country with an advanced welfare state. However, data from across western countries indicates that health inequalities persist even within a context of welfare provision (Marmot, 2017, 2017; Marmot & Wilkinson, 2005; Wilkinson & Pickett, 2017a, 2017b). Arguments have been proposed that while welfare provision has undoubtedly assisted in improving the material conditions of society, it may have also decreased their relative impact on health outcomes. As a result, the persistence of health gradients may be due to immaterial factors such as personality characteristics, social and cultural capital, or cognitive ability (Mackenbach, 2012). Given this, the co-occurrence of hardship and poor mental health may be driven by the indirect impact of 'third' variables or latent traits (Hudson, 2005; Pampel et al., 2010).

Collectively, these results have important implications for interventions designed to improve population mental health. People who tend to experience financial hardship appear to be distinct from those who do not. Moreover, the mental health of each of these groups diverges substantially. Thus, along with differences in long-term hardship profile, identifying related socioeconomic factors which differentiate these groups is crucial for informing both the content and targeting of intervention efforts. The finding that membership within hardship states is highly stable is also cause for concern. Principally as this indicates that hardship can become entrenched and difficult to escape from – a finding that has been commonly observed within the poverty literature over many years (Cellini et al., 2008; Jenkins & Siedler, 2007; Smith & Middleton, 2007). For example, prior work has shown that up to half of all people who fall into poverty in the United States will remain below the relative income poverty line in at least five of the ensuing ten years (Stevens, 1999). Additionally, given the substantial between-person differences identified within this body of work, clinical treatment and/or short-term financial support may be less impactful on population mental health than broader social and economic policies designed to interrupt cycles of intergenerational poverty and long-term entrenched financial hardship.

Policy and Practice Implications

The findings presented in this thesis have important implications for policy and practice aimed at improving population mental health. Firstly, this work extends a vast and compelling body of evidence that has repeatedly demonstrated the substantial link between socioeconomic disadvantage and poor mental health over many decades (Allen et al., 2014; Kessler & Cleary, 1980; Ridley et al., 2020; WHO, 2024). Within the context of stable, or even rising, rates of mental disorders across western developed countries (Jorm et al., 2017; Mulder et al., 2017; Ormel et al., 2020) it is reasonable to question whether the advice of this literature has been heeded and effectively integrated into policy, interventions, preventative frameworks, or clinical practice guidelines designed to reduce the burden of illness associated with mental disorders. Broadly speaking, this is reflective of a tendency for mental health policy to focus *downstream* on individuals, service access, and treatment availability, and much less on preventing exposure to *upstream* determinants (Faust & Menzel, 2011; Jorm, 2014; Reavley & Jorm, 2014; Shim & Compton, 2018; Wykes et al., 2015b). The findings of this thesis, together with the broader literature, have the potential to inform policies oriented towards improving population mental health by more directly addressing its structural determinants.

As touched upon in the introduction to this thesis, significant resources have been allocated towards improving access to mental health treatment within Australia. This is evident with respect to the quantity of trained mental health professionals, the quantity of available services, and expanded access to treatments such as psychotherapy, pharmacological medications, and counselling (Jorm, 2018). However, in the context of discussing the relationship between an individual's socioeconomic environment and their mental health, specific limitations to treatment expansion should be acknowledged. Principally, increased treatment does not directly alter the socioeconomic conditions in which an individual is exposed. Moreover, where effective treatment is received, its efficacy may be substantially undermined by the ongoing exposure to risk factors associated with socioeconomic disadvantage. In certain cases, particularly with respect to individuals in highly deprived circumstances, they will continue being exposed to the same risk factors that originally diminished their mental health. This is certainly not to say that treatment is ineffective, nor that its expansion is mistaken. The provision and continued expansion of efficacious treatment is undoubtedly essential for individuals experiencing poor mental health, particularly given its potential to reduce suffering by shortening time to recovery. Moreover, the preferable allocation of resources to increasing treatment access is understandable given the relative scalability and actionability of doing so in comparison to the challenges inherent with broad-scale social and economic change (Ormel et al., 2020). Instead however, this speaks to the necessity of treatment being complemented with measures that can also attenuate exposure to factors we now understand as posing a significant risk to mental health.

For example, strengthening income support payments is one such possibility. Botha and colleagues (2022) demonstrated that supplemental income payments provided to Australians during the beginning of the COVID-19 pandemic significantly reduced financial stress, which in turn protected mental health. Permanent increases to income support and improvements to how welfare payments are indexed may help to protect households from experiencing hardship during economic shocks. As a result, this may also mitigate episodes of poor mental health that result from ebbs and flows in income and employment (Barr et al., 2012; Olesen et al., 2013; Stuckler et al., 2009). More broadly, evidence from quasi-experimental studies of Native American tribes who opened casinos has demonstrated the positive impact to mental health of increased income (Costello et al., 2003; Wolfe et al., 2012). Similarly, cash transfers in low- and middle-income countries have shown effectiveness in alleviating depression and anxiety (Wollburg et al., 2023). While research from the United Kingdom has highlighted that the introduction of a National Minimum Wage significantly improved the mental health of low-wage workers, and that these improvements were mediated through a reduction in financial strain (Reeves et al., 2017).

With respect to clinical practice, calls have been made to embed financial counselling, including advice on managing and overcoming debt, into standard clinical care for people experiencing both mental health problems and financial difficulties (Evans, 2018). To date, empirical evidence detailing the efficacy of finance-based interventions aimed at improving clinical and psychosocial outcomes is limited (Tsai et al., 2024). Nonetheless, upskilling psychologists and other mental health professionals to assist patients presenting with mental disorders and financial difficulties may be an effective way to improve existing modes of one-on-one clinical care and overall treatment outcomes. This is particularly germane in light of the results presented within this thesis – highlighting the co-occurrence of financial hardship and poor mental health – along with prevailing work demonstrating that people with a mental disorder are significantly more likely to be in debt than the rest of the population (Jenkins et al., 2008), and significantly less likely to recover if experiencing financial difficulties compared to those who are financially stable (Skapinakis et al., 2006). At a minimum, clinicians should be encouraged to screen clients for financial hardship experience, and to be aware of the substantial association between poor mental health and socioeconomic disadvantage, including the greater likelihood of experiencing financial hardship.

Narrowing the focus to Australia, national policy addressing the dramatic rise in housing costs is essential. House prices in Australia have increased at a significantly faster rate than both wages and CPI over the past three decades (Pawson et al., 2020, p. 53). This presents a major challenge to alleviating financial hardship, as housing costs typically constitute the largest component of household expenditure. As a result, they have a disproportionate impact on household budgets, disposable income, and the ability for households to save.

However, tackling housing affordability in Australia will not be straightforward. Housing has become a vital component of financial markets as residential mortgages contribute significantly to gross domestic product (Aalbers, 2016; Rolnik, 2013). Moreover, for more than three decades housing policy in Australia has focused on generous demand-side subsidies designed to incentivise home ownership. This includes first home buyer assistance programs, and substantial tax benefits in the form of 'negative gearing' and capital gains tax discounts (Adkins et al., 2021; Christophers, 2021; Morris, 2023). In concert with weakened tenancy rights and progressively reduced investment in social housing, these policies have led to a substantial rise in house prices. In turn, home ownership rates have declined, particularly amongst younger Australians – for whom significant declines in mental health have also been observed (Burns et al., 2020; Morris, 2023; Slade et al., 2024). However, many homeowners, having benefited tremendously from the prevailing housing policies, have a vested interest in maintaining the status quo (Australian Bureau of Statistics, 2021c). Furthermore, home ownership remains a crucial, albeit unofficial, 'fourth pillar' of the Australian pension system. The income adequacy of the government Age Pension is dependent on retirees being outright homeowners, which further complicates substantive changes to housing policy (Bradbury & Saunders, 2022; Saunders, 2017; Saunders et al., 2022b). Given this, policy solutions must be nuanced. Nonetheless, proponents of reform advocate for investment in significantly expanded social housing, amendments to the rental market and tenancy rights, and restructuring of housing-related tax concessions (Daley & Wood, 2016; Gurran et al., 2018; Martin et al., 2022).

In line with the inherent challenge of addressing housing costs in Australia, lie the broader difficulties of implementing a substantive program of mental health risk reduction. In principle, the majority of socioeconomic risk factors to mental health are modifiable. However, in practice, many risks are a product of governmental policy at local, national, and international levels, which then intersect with the commercial interests of profit-driven corporations, technological developments, and constant geopolitical change (Ormel et al., 2020). Moreover, the pathways through which people can fall into poverty or experience financial hardship are multiple, interconnected, cumulative and complex (Figueroa et al., 2020). This spans exposure to stressors, abuse, and maladaptive environments in childhood, to poor health curtailing employment opportunities in adulthood, and lower educational outcomes limiting opportunities for upward social mobility (Braveman & Gottlieb, 2014; Grummitt et al., 2024; Kirkbride et al., 2024). As opposed to single policy changes, reducing financial hardship with the express goal of improving population mental health will require a suite of overlapping policies that comprehensively addresses multiple risk factors at the individual and societal levels. To be successful, Ormel and Emmelkamp (2023) have argued that prevention will have to be "structural, well-funded, long-term, socially embedded, starting at an early age, addressing both parenting, kids, and schools, and combining universal (health promotion) and indicated/selective prevention". Such an approach differs from selective intervention that is focused upon those identified as high risk or socioeconomically disadvantaged. Consistent with this, various frameworks for improving population health have been proposed. Geoffrey Rose argued that lowering the *entire* populations exposure to known health risk factors would produce greater population level improvements to health than targeting only high-risk individuals (Rose, 1985; Rose & Day, 1990). Similarly, Marmot's principle of proportionate universalism advocates that action to address population health should be universally implemented across the entirety of a population, but comprise a scale and intensity proportionate to the level of disadvantage experienced by varying sub-groups (Marmot et al., 2010).

Strengths and Limitations

The empirical work presented in this thesis is defined by several key strengths. While the specific merits of each analysis have been discussed within each respective chapter, there exist several broad strengths that define this body of work as a whole.

Firstly, a series of methodological strengths characterise this work. The systematic review comprised 94 studies, which covered 26 countries and included close to 500,000 participants. Along with the overall strength and consistency of the association between financial hardship and mental that emerged from this analysis, the findings can be considered highly robust given the inherent methodological characteristics of the review itself. The three ensuing empirical analyses all made use of the HILDA survey. The strengths of this long-running panel survey have been expanded upon throughout this thesis. Nonetheless, in summary the HILDA survey contains very high quality, nationally representative panel data from over 17,000 respondents in Australia. Data has been collected annually, every year, since 2001, and re-interview rates have commonly exceeded 93%. The combination of detailed demographic, economic, and health measures make possible sophisticated analyses of the drivers and consequences of a vast range of health outcomes in Australia. In particular, a recent study highlighted the HILDA surveys virtues as a cornerstone of Australian mental health research. It demonstrated that close to 20% of all identified papers published between 2002 and 2020 that used HILDA survey data, comprised a significant focus on mental health (Butterworth et al., 2021). With regard to more specific benefits of HILDA, it contains a sample that is broadly representative of the Australian population, which allows researchers to draw insights that are generalisable at the national level. Moreover, given its longitudinal design, it contains repeated measures from the same individuals over long spans of time. This enables the disaggregation of cohort from period effects, the ability to control for fixed and varying characteristics of individuals, the separation of between- from within-person effects, and the application of life-course analytic techniques to examine how various processes unfold across time – all approaches which have been utilised throughout this thesis. Additionally, the variables used to assess the focal relationship of this work – specifically, the 7-item measure of financial hardship, and the MHI-5 component of the SF-36 used to measure mental health – have demonstrated reliability and validity over several decades of research (Bray, 2001; Butterworth et al., 2012; Butterworth & Crosier, 2005; Crowe et al., 2016; Kiely et al., 2015; Ware et al., 1993; Ware & Sherbourne, 1992). The specific benefits of measuring socioeconomic disadvantage using an outcome-based measure of financial hardship have been detailed comprehensively in the general introduction. In short, outcome-based approaches overcome a range of limitations associated with income-based assessments of socioeconomic disadvantage as they assess the *actual* consequences of insufficient financial resources (Bray, 2001; Mack & Lansley, 1985). Finally, the use of longitudinal analytic techniques in each of the three empirical chapters, maximised the longitudinal structure of the HILDA survey. The primary benefit of these approaches is that they move analysis beyond static cross-sectional associations between people at a specific point in time, and enable an examination of how a process of interest unfolds within individuals over time. This particular strength was leveraged through the use of sophisticated random-intercept cross-lagged panel models, within-between mixed-effects (Mundlak) models, social sequence analysis, and latent Markov modelling.

Beyond methodological characteristics, a key strength of this empirical work lies in its positioning at the intersection of broad frameworks encapsulating macro and micro social determinants of health, economics, psychology, and biology. This inter-disciplinary approach informed the key research questions and has guided interpretation of results. The goal of integrating knowledge and insight from varying fields was to ensure research questions were relevant and understood through the lens of present economic and political realities. More broadly, the introduction of this thesis detailed that the majority of evidence from high-income developed countries suggests that population mental health has not improved over the past 30 years. Novel thinking is required to understand what is driving this trend and how it can be interrupted. Population mental health is downstream of a complex array of interacting social, psychological, biological, and economic factors. Therefore, it is naturally pre-disposed to the kind of interdisciplinary inquiry at the heart of this thesis.

Some overarching limitations to this body of work should also be noted. While the strengths of the HILDA survey are numerous, limitations do exist. Principally, it is difficult to make strong causal claims from panel survey data. Moreover, as with any longitudinal panel, the HILDA survey is afflicted by attrition. Survey weights can be used to reduce the impact of this. However, beyond the analysis that examined the long-term prevalence of financial hardship and its two sub-dimensions, survey weights were not used. Reasons for this included prevailing technical limitations with R software packages, and the complexity of incorporating survey weights being beyond the scope of this work.

Additionally, limitations pertain to the focal measures used in each analysis. In particular, the measure of financial hardship is self-reported. This may lead to under-reporting due to social desirability and the stigma associated with experiencing socioeconomic disadvantage. Similarly, the MHI-5 scale from the SF-36 used to assess mental health is also a self-report scale. Therefore, discrepancies may arise compared to formal clinical assessments conducted by trained clinical psychologists. Moreover, the reference timeframes of the two measures used to assess financial hardship and mental health were different. Specifically, financial hardship was assessed over the past twelve months, whereas the MHI-5 assessed mental health over the preceding four weeks. The implications of this have been discussed in detail throughout the empirical chapters. Nonetheless, this may have obscured analyses of temporality, and reduced the strength of observed associations. With respect to temporality, it has been observed throughout this work that the one-year interval between survey waves may also mask important within-year dynamics between financial hardship and mental health.

It should also be noted that financial hardship was defined by affirming the experience of just one of the seven items comprising the utilised scale. Research in Australia using this scale has commonly employed this approach (Butterworth & Crosier, 2005; Kiely et al., 2015). Nonetheless, the observed association with mental health may vary with differing thresholds of how many, and which items must be affirmed to constitute hardship. Additionally, the HILDA survey does not contain a measure of financial hardship in 2010. This minor gap prevents an analysis of hardship and its impact upon mental health in the period following the global financial crisis.

More broadly, another limitation of the analyses conducted across this thesis was the absence of measures specifically assessing personality, cultural, and genetic factors that may also influence mental health (Frankham et al., 2020). It is therefore possible that the observed relationship between financial hardship and mental health may be confounded by unmeasured variables.

Future Research

The findings within this thesis open up numerous pathways for further research. Several ways in which this work can be extended have been discussed in detail within each empirical chapter. Many of these directions comprise natural refinements and expansions to the conducted analyses. These include: (1) examining how the association with mental health varies according to alternative measures, specific items, or common clusters of hardship; (2) examining the sequence in which hardships emerge, including whether particular hardships tend to occur first, or whether the experience of certain hardships trigger the experience of others; (3) assessing the degree to which different hardships share a temporal relationship with events such as job loss, family formation, education, and spells of good or bad health; (4) examining pathways mediating the relationship between financial hardship and mental health; (5) assessing the impact of time-varying confounders on temporal aspects of the relationship between financial hardship and mental health; and (6) examining the degree to which key sociodemographic factors predict membership of and transitions between, latent financial hardship states.

Numerous additional pathways building upon this thesis could also be explored. A highly salient future direction is a focus on exploring intergenerational aspects of the relationship between financial hardship and mental health. In other words, to what extent is parental experience of *financial hardship* associated with the experience of financial hardship and/or poor mental health in offspring? Similarly, to what extent is parental experience of *poor mental health* associated with financial hardship and/or poor mental health in offspring? The persistence of poverty across generations has been well documented – as has its attendant health consequences (Bavaro et al., 2024; Hamad et al., 2024; Wagmiller & Adelman, 2009). Moreover, recent research has also identified that differences in socioeconomic outcomes persist even after controlling for factors like education. For example, first generation university graduates from families of lower-class backgrounds in the United States report poorer earnings and job progression than their colleagues from families of higher-class backgrounds. Moreover, this effect remained, even when comparing individuals holding PhD level qualifications (Stansbury & Rodriguez, 2025). A similar result has also been demonstrated using data from the United Kingdom. Specifically, after controlling for the field and place of study, graduates from families with higher incomes reported greater earnings than graduates from families of lower incomes (Vignoles et al., 2016). Further research exploring the mechanisms driving these effects is crucial, in order to identify ways to break intergenerational cycles of disadvantage and poor mental health.

To help explain these intergenerational cycles, future research could explore the extent to which the distribution of mental health outcomes can be explained by *Matthew Effects* (Bask & Bask, 2015). This would involve quantifying the degree to which initial socioeconomic advantage or disadvantage sets people on trajectories that are reinforced over time and lead to increasingly divergent mental health outcomes. Specifically, such work could seek to (1) identify whether there exists specific resource threshold effects from which mental health outcomes significantly diverge; (2) determine whether particular socioeconomic factors contribute significantly more or less variability to the divergence of health outcomes over time; (3) identify whether the presence or absence of specific socioeconomic factors have a cumulative positive or negative effect on mental health over time; and (4) identify whether the presence or absence of specific socioeconomic advantages or disadvantages significantly impedes good mental health.

There is also the outstanding question of whether financial hardship causes poor mental health, or whether poor mental health causes financial hardship. The inherent limitations of longitudinal panel survey data preclude strong causal claims. Given this, research leveraging natural experiments, quasi-experiments, and approaches such as Mendelian randomisation are needed to provide an opportunity for causal effects to be studied, and for causality within this relationship to be inferred.

Future work should also seek to conduct cross-national comparisons of hardship prevalence. Alongside the HILDA Survey exist a range of longitudinal household panel surveys from around the world. These include the British Household Panel Survey and UK Household Longitudinal Survey (United Kingdom), Korean Labor & Income Panel Study (South Korea), Russia Longitudinal Monitoring Survey (Russia), Swiss Household Panel (Switzerland), Panel Study of Income Dynamics (United States) and the German Socio-Economic Panel (Germany). Comparative analysis of these surveys would enable an examination of hardship rates across different countries. It would also facilitate an assessment of whether the association between financial hardship and mental health varies by cultural context, healthcare system, or welfare regime.

Conclusion

Concerted efforts to reduce the burden of disease associated with mental disorders have been pursued within Australia over the past thirty years. This is evident in substantially increased public funding to the mental health sector, expanded availability of services and treatments, and significant increases to the mental health workforce. Concerningly, these efforts have not coincided with a measurable improvement in the mental health of the population – rates of mental disorders have remained stable, or even increased since the mid 1990's. A range of explanations have been proposed to explain why the prevalence of mental disorders has not declined within this context of significantly expanded treatment and resourcing. It is the position of this thesis, that attention should be turned to a broader set of modifiable factors, in order to identify mechanisms through which the persistent rates of mental disorder may be interrupted and ultimately reduced. This body of work focused upon the substantial evidence demonstrating a consistent link between socioeconomic disadvantage and poor mental health. Specifically, the empirical analyses sought to extend prevailing findings by advancing our knowledge of the relationship between financial hardship – an outcome-based measure of socioeconomic disadvantage – and mental health.

A systematic review and three empirical analyses were conducted to examine various aspects of this relationship. Collectively, these studies overwhelmingly demonstrated the substantial link between financial hardship and mental health. The consistency and strength of this association was evident across international literature included and synthesised in the systematic review. Furthermore, this finding was confirmed within the Australian context using nationally representative data and various analytic approaches. Financial hardship was also found to affect a sizeable minority of the Australian population with evidence to suggest that its impact upon mental health was largely contemporaneous. However, subsequent analyses revealed a significant separation between people who rarely, if ever, experienced hardship, and those who experienced relatively persistent hardship. Substantially worse mental health was observed in the group defined by persistent financial hardship, compared to those for whom hardship was only fleeting or absent. Additional analysis examined the existence of latent financial hardship states, the likelihood of transitioning between them, and the mental health implications of doing so. Transitions into higher risk financial hardship states were associated with declines in mental health, while transitions into lower risk financial hardship states were associated with mental health improvements.

These findings add to a substantial and highly compelling evidence base that has consistently highlighted the association between socioeconomic disadvantage and poor mental health. It remains an open question to what extent this evidence has been heeded in the past. However, the extent to which it is heeded going forward may be critical for the mental health of an entire generation. The findings contained within this thesis, and the implications for preventative action that follow, come at a time of trepidation. House prices in Australia have skyrocketed. Income and wealth inequality have been slowly but steadily increasing for several years. Precarious modes of employment are increasingly prevalent. The mental health of teenagers and adolescents has been consistently deteriorating for at least a decade. Yet, it is evident that a substantial link exists between the socioeconomic conditions that contextualise our day-to-day lives and our mental health. By many metrics the current trend in these socioeconomic conditions may be one of decline. Therefore, policy aimed at improving national mental health may be far more efficacious if it seeks to address these very socioeconomic conditions, including reducing the prevalence and severity of financial hardship, experienced by a sizeable proportion of the population.

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Appendices

Appendix A – Supplementary Material for Chapter 2

Appendix A.1

Database specific search terms used.

Database	Search Strategy
PubMed	
1	("mental health" OR "mental illness*" OR "mental disorder*" OR "affective disorder*" OR "anxiety" OR "depression" OR "stress" OR "distress" OR "emotional Problem*" OR "mood disorder*" OR "psychological distress" OR k10)
2	AND ("financial hardship*" OR "financial strain*" OR "financial distress" OR "financial deprivation*" OR "financial difficult*" OR "economic hardship*" OR "economic disadvantage" OR "economic deprivation*" OR "poverty" OR "debt")
3	AND (longitudinal OR "panel stud*")
Scopus	
1	(TITLE-ABS-KEY ("mental health" OR "mental illness*" OR "mental disorder*" OR "affective disorder*" OR "anxiety" OR "depression" OR "stress" OR "distress" OR "emotional Problem*" OR "mood disorder*" OR "psychological distress" OR k10)
2	AND TITLE-ABS-KEY ("financial hardship*" OR "financial strain*" OR "financial distress" OR "financial deprivation*" OR "financial difficult*" OR "economic hardship*" OR "economic disadvantage" OR "economic deprivation*" OR "poverty" OR "debt")
3	AND TITLE-ABS-KEY (longitudinal OR "panel stud*"))
4	AND (LIMIT-TO (LANGUAGE , "English"))
OVID	
(PsycINFO / Embase / MEDLINE)	
1	mental health.mp. or exp Mental Health/
2	mental illness*.mp.
3	exp Mental Disorders/ or mental disorder*.mp.
4	exp Affective Disorders/ or affective disorder*.mp.
5	exp Anxiety/ or anxiety.mp.
6	exp Major Depression/ or depression.mp.
7	stress.mp. or exp Stress/
8	exp Distress/ or distress.mp.
9	exp Emotional Disturbances/ or emotional problem*.mp.
10	mood disorder*.mp.
11	psychological distress.mp.
12	K10.mp.
13	1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12
14	financial hardship*.mp.
15	financial strain.mp. or exp Financial Strain/
16	financial distress.mp.
17	financial deprivation.mp.
18	financial difficult*.mp.
19	economic hardship.mp.
20	economic disadvantage.mp. or exp Economic Disadvantage/
21	economic deprivation.mp.
22	poverty.mp. or exp Poverty/
23	debt.mp.
24	14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23
25	exp Longitudinal Studies/ or longitudinal.mp.
26	panel stud*.mp.
27	25 or 26
28	13 and 24 and 27

Appendix A.2

Summary of systematic review exclusion criteria.

Exclusion Criteria	
Study Characteristics	
1	No study abstract available to review.
2	Study is not available in full text format.
3	Study is not available in English language.
4	Study is a meta-analysis or systematic review.
5	Study is not an original research paper (i.e., a Protocol paper, Editorial, Opinion, Comment, Correspondence piece or Letter to the Editor).
6	Study is a preprint, grey literature, dissertation, or have not been peer reviewed.
Sample Composition	
7	Study analyses a clinical sample (i.e., a sample that is selected on the basis of a pre-existing health condition).
8	Study uses convenience sampling methodologies (such as snowballing, purposive sampling, quota sampling, accidental sampling, or volunteer sampling; have been advertised online/via social media, or used crowdsourcing data collection platforms like MTurk).
Measures & Methodology	
9	Study does not use prospective longitudinal data (i.e., if they use a single data wave, a retrospective longitudinal design, or a repeated cross sectional design).
10	Study does not analyse study data longitudinally (e.g., if a repeated cross sectional analysis has been conducted).
11	Study does not contain a measure of common mental health conditions.
12	Study does not contain a measure of common mental health conditions as an outcome in any analysis.
13	Study does not measure financial hardship at the level of the individual (i.e., studies will be excluded if they only measure financial hardship at a familial or neighbourhood level).
14	Study measures financial hardship using income alone, using an income derived measured of hardship (i.e., relative poverty that is measured as some ratio of median income), or infer hardship according to an objectively defined indicator (i.e., lack of a vehicle, or according to housing tenure).
15	Study does not, in any analysis, test the association between financial hardship and a common mental health condition.
16	Study measures an indirect association between financial hardship and mental health across generations or between different individuals (i.e., where financial hardship is reported by parents and mental health outcomes are reported by their children).

Appendix A.3

Reference list of included studies – in ascending order by publication year.

Krause, N. (1987). Chronic strain, locus of control, and distress in older adults. *Psychology and Aging, 2*(4), 375–382. https://doi.org/10.1037/0882-7974.2.4.375

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Appendix A.4

Detailed sample characteristics of included studies.

Sample Characteristics	n	%	Papers
Sample Size			
100 - 249	5	5.3%	94
250 - 499	9	9.6%	94
500 - 999	14	14.9%	94
1,000 - 1,999	14	14.9%	94
2,000 - 2,999	16	17.0%	94
3,000 - 4,999	11	11.7%	94
5,000 - 9,999	9	9.6%	94
10,000 - 19,999	11	11.7%	94
20,000 - 45,000	5	5.3%	94
% Males in Sample			
0	15	17.4%	86
0 - 10	0	0.0%	86
10 - 20	2	2.3%	86
20 - 30	4	4.7%	86
30 - 40	11	12.8%	86
40 - 50	36	41.9%	86
50 - 60	11	12.8%	86
60 - 70	2	2.3%	86
70 - 80	2	2.3%	86
80 - 90	1	1.2%	86
90 - 100	2	2.3%	86
Age			
Min	12		63
Max	76		63
Average	45.5		63

Appendix A.5

Surveys/datasets used within included studies.

Survey / Dataset	Country	n
* Not Stated / Not Named		14
1958 National Child Development Study	United Kingdom	1
1970 British Cohort Study (BCS70)	United Kingdom	1
2000 Psychiatric Morbidity Survey	United Kingdom	1
Alameda County Study	United States of America	2
Annual Living Conditions Survey (ULF)	Sweden	1
Arizona Pathways to Life Success for University Students (APLUS)	United States of America	1
Australian Longitudinal Study on Women's Health (ALSWH)	Australia	1
Australian National COVID-19 Mental Health, Behaviour and Risk Communication Survey	Australia	1
Australian Rural Mental Health Study (ARMHS)	Australia	3
Born in Bradford Study	United Kingdom	1
British Household Panel Study (BHPS)	United Kingdom	1
Building a New Life in Australia Study (BNLA)	Australia	2
California Families Project	United States of America	1
Canadian Quality of Work and Economic Life Study (C-QWELS)	Canada	1
Canadian Work, Stress, and Health Study (CAN-WSH)	Canada	1
Child Development Study (CDS)	Côte d'Ivoire; Ghana	1
Chinese Longitudinal Healthy Longevity Survey (CLHLS)	China	1
Corona Immunitas Digital Follow-Up (CI-DFU)	Switzerland	1
COVID-19 Social Study	United Kingdom	1
COVID-19 survey (UK)	United Kingdom	1
Early Childhood Longitudinal Study-Birth Cohort (ECLS-B)	United States of America	1
European Longitudinal Cohort Study of Pregnancy and Childhood - Czech (ELSPAC-CZ)	Czech Republic	1
Family and Community Health Study (FACHS)	United States of America	1
Fragile Families and Child Wellbeing Study (FFCWS)	United States of America	3
German Socio-Economic Panel (SOEP) study	Germany	1
GoWell	Scotland	1
Growing Up in Ireland	Ireland	1
Health and Retirement Study (HRS)	United States of America	1
Household Income and Labour Dynamics of Australia Survey (HILDA)	Australia	4
Iowa Youth and Families Project (IYFP)	United States of America	1
Korea Welfare Panel Study (KOWEPS)	South Korea	4
Life Course Perspective and Dropout from Higher Education (LAST)	Germany	1
Life Patterns	Australia	1
Longitudinal Midlife in the United States (MIDUS) study	United States of America	1
Miami Disability Study	United States of America	1
National Income Dynamics Study–Coronavirus Rapid Mobile Survey (NIDS-CRAM)	South Africa	1
National Longitudinal Study on Alcohol and Related Conditions (NESARC)	United States of America	2
National Population Health Survey (NPHS)	Canada	1
Netherlands Study of Depression and Anxiety (NESDA)	Netherlands	1
Panel study of Belgian Households (PSBH)	Belgium	1
Personality and Total Health (PATH) Through Life	Australia	3
PIONEER-COVID-19 study	Singapore	1
Resources for Enhancing Alzheimer's Caregiver Health (REACH)	United States of America	1
Rural Families Speak (NC-223)	United States of America	1
Southampton Women’s Survey (SWS)	United Kingdom	1
Stockholm Public Health Cohort (SPHC)	Sweden	1

Survey of Family, Income and Employment (SoFIE)	New Zealand	1
Swedish Level of Living Survey (LNU)	Sweden	1
Swedish Panel Study of Living Conditions among the Oldest Old (SWEOLD)	Sweden	1
Swiss Household Panel (SHP)	Switzerland	1
Taiwan Database of Children and Youth in Poverty (TDCYP)	Taiwan	1
Taiwan Longitudinal Study on Aging (TLSA)	Taiwan	2
Trajectoires Epide´Miologiques en POpulation (TEMPO) - Additional COVID-19 survey	France	1
Trends and Implications of Poverty and Social Disadvantages in Hong Kong	China	1
UK Household Longitudinal Study - COVID-19 Survey (UKHLS)	United Kingdom	1
UK Household Longitudinal Study (UKHLS)	United Kingdom	1
Welfare, Children, and Families Project (WCF)	United States of America	2
Well-Being Survey	United States of America	1
Whitehall II	United Kingdom	2
WHO-SAGE Survey (Ghana Component)	Ghana	1
Women's Employment Study (WES)	United States of America	2
Yale Health and Ageing Project (YHAP)	United States of America	1
Young Lives Study	Ethiopia; India; Peru; Vietnam	2

Appendix A.6

Detailed Study Characteristics

Study Characteristic	n
Publication Year	
1987	1
1989	1
1994	1
1996	1
1997	1
1999	1
2000	1
2002	2
2003	1
2004	1
2005	1
2006	1
2007	2
2008	1
2009	5
2010	2
2011	4
2012	1
2014	4
2015	4
2016	6
2017	3
2018	9
2019	4
2020	7
2021	12
2022	13
2023	4
Survey Setting	
Local	19
Regional	18
Regional; Local	2
National	53
International	2
Survey Waves	
Average	4.1
2	32
3	26
4	15
5	7
6	3
7	1
8	2
9	2
10	2
12	1

19	2
20	1
Survey Wave Interval (Months)	
Average	19.1
0.25	2
0.5	1
1	2
2	1
3	4
4	5
5	1
6	8
8	1
9	3
12	27
18	3
24	18
36	10
48	3
60	1
72	1
96	1
108	1
Study Span (Years)	
Average	5.4
0-1	16
1-2	13
2-3	10
3-4	10
4-5	7
5-6	5
6-7	4
7-8	5
8-9	4
9-10	1
10-11	1
11-12	3
13-14	3
15-16	1
16-17	1
17-18	2
18-19	1
23-24	1

Appendix A.7

Age ranges of included studies.

Min \ Max	14	15	17	18	19	21	22	24	26	29	34	39	43	46	47	53	54	55	57	60	62	64	65	68	74	76	80	84	85	96	+	Total
10	1																															1
12				1																											1	2
13		1										1																				2
14			1				1																								1	3
15													1					1		1											2	5
16					1																			1	1						2	5
17																			1													1
18						1			1	1		1		1		1	2					1	1		1						15	26
19																									1						2	3
20							1	1			2																			1		5
21										1																						1
24																								1								1
25																						2					1				1	4
26																													1			1
27															1																	1
30																												1				1
35																		1														1
40																						1										1
50																					1										5	6
53																										1						1
60																															3	3
64																								1								1
65																															5	5
Total	1	1	1	1	1	1	2	1	1	2	2	2	1	1	1	1	2	2	1	1	1	4	1	3	3	1	1	1	1	1	37	80

Legend	Yr. Span (relative)
10-18 (Adolescence)	
10-39 (Adolescence to Young Adults)	
19-39 (Young Adults)	
10-65 (Adolescence to 65)	
19-65 (Young Adults to 65)	
40-65 (Midlife)	
10-65+ (Adolescence to Old Age)	
19-65+ (Young Adults to Old Age)	
40-65+ (Midlife to Old Age)	

The minimum age of the assessed range is listed down the page, and the maximum age in the range is listed across the page.

Appendix A.8

Detailed description of financial hardship measures used within each study.

Author(s)	Pub. Year	Description of Measure used to Assess Financial Hardship
Krause N,	1987	Measured with a four-item scale taken from the work of Pearlin et al. (1981). The items in this scale assessed whether respondents felt that they have enough money for food, medical care, clothing, or leisure activities.
Jones L,	1989	The Perceived Economic Deprivation Scale (PEDS). This scale measures relative changes in savings, debts, and patterns of consumption (Aiken & Ferman, 1966).
Mendes De Leon C, Rapp S, Kasl S	1994	Financial strain. Measured by a 4-item scale adopted from Pearlin et al. (1981). This scale assesses whether respondents have enough money to afford 1. the kind of food and 2. the medical care they (and their spouses) should have, 3. how much difficulty they have in meeting monthly payments on their bills, and 4. whether they could make ends meet at the end of the month or whether they had any money left over.
Vinokur A, Price R, Caplan R	1996	Financial strain. Measured using a 3-item index (Kessler et al., 1988; Vinokur & Caplan, 1987) based on answers to three questions with 5-point rating scales. The questions asked: 1. "How difficult is it for you to live on your total household income right now?"; 2. "In the next two months, how much do you anticipate that you or your family will experience actual hardships such as inadequate housing, food, or medical attention?"; 3. "In the next two months, how much do you anticipate having to reduce your standard of living to the bare necessities of life?".
Roberts R, Kaplan G, Shema S, Strawbridge W	1997	Financial problems (not defined in text)
Conger R, Conger K, Matthews L, Elder G	1999	Adolescent Hardship Experiences. Adolescents responded to two questions about their hardship experiences in relation to school and friends. Each question asked how often they had enough money for 1. clothes, school activities, or other things, and 2. doing things, such as going to the movies, eating pizza, etc. Rating were made on a 5-point scale - 1 = always; 5 = never.
Roberts R, Shema S, Kaplan G, Strawbridge W	2000	Financial Strain. Assessed using five items that recorded how many times there was not enough money to buy clothes, fill a prescription, see a doctor, pay rent or mortgage, or buy food. Not having enough money for any item was classified as financial strain.
Lai J, Chan R	2002	Measured using a three-item index (Vinokur & Caplan, 1987). Using 5-point scales (1 = not at all difficult; 5 = extremely difficult), participants rated 1. "How difficult is it for you to live on your total household income right now?" 2. "How much would not having another job in the next two months create actual hardships for you and your family, such as inadequate housing, food, or medical attention?" 3. "How much would not having another job in the next two months reduce your standard of living to the bare necessities of life?".
Price R, Choi J, Vinokur A	2002	Measured using a three-item index (Vinokur & Caplan, 1987). Using 5-point scales (1 = not at all difficult; 5 = extremely difficult), participants rated 1. "How difficult is it for you to live on your total household income right now?" 2. "How much would not having another job in the next two months create actual hardships for you and your family, such as inadequate housing, food, or medical attention?" 3. "How much would not having another job in the next two months reduce your standard of living to the bare necessities of life?".
Waters L, Muller J	2003	Assessed using a single-item measure taken from Messer and Harter (1986): "I feel that I do not have enough money to provide for the material necessities of life". Participants responded on a 5-point scale.
Siefert K, Heflin C, Corcoran M, Williams D	2004	Food insufficiency. Defined as restricted household food stores, or too little food intake among either adults or children in the household (Scott and Wehler 1998). Operationalised using the question, "Which of the following describes the amount of food your household has to eat: 1. enough to eat; 2. Sometimes not enough to eat; 3. Often not enough to eat?"
Heflin C, Siefert K, Williams D	2005	Food insufficiency. Defined as restricted household food stores, or too little food intake among either adults or children in the household (Scott and Wehler 1998). Operationalised using the question, "Which of the following describes the amount of food your household has to eat - enough to eat, sometimes not enough to eat, or often not enough to eat?"
Skapinakis P, Weich S, Lewis G, Singleton N, Araya R	2006	Economic Hardship. Participants were asked three questions about their ability to pay for everyday needs in the preceding year. This included questions on 1. Whether they were seriously behind in paying bills, credit card debts, mortgage repayments, or loans; 2. Whether they had been subjected to disconnection by a utility company or had used water, gas, electricity or the telephone less because they could not afford; 3. Whether they had borrowed money from unofficial sources in order to pay for their everyday needs. People reporting at least one difficulty were classified as having experienced financial difficulties.
Ahnquist J, Fredlund P, Wamala S	2007	Financial stress. Measured using two variables: inability to pay ordinary bills (e.g., food or rent), and having a lack of cash reserves (difficulty in raising 10,000 SEK within a week if anything unpredictable occurs).
Lorant V, Croux C, Weich S, Deliège D, Mackenbach J, Ansseau M	2007	Subjective financial strain. Assessed with the question: "How well are you managing these days with your current income?". (0 = very well; 5 = with great difficulty).
Dunn N, Inskip H, Kendrick T, Oestmann A, Barnett J, Godfrey K, Cooper C	2008	Perceived Financial Strain. Assessed with the question: "How well would you say you are managing financially these days?". 1. Living comfortably; 2. Just about getting by; 3. Finding it difficult or very difficult.

Butterworth P, Rodgers B, Windsor T	2009	In wave 1, financial problems assessed by inquiring whether: 'The respondent (or their family) had gone without things they really needed in the last year because they were short of money'. In wave 2, financial problems were assessed using four items: 'Over the past year have the following happened because you were short of money?': 1. Pawned or sold something; 2. Went without meals; 3. Unable to heat home; 4. Asked for help from welfare/community organisations. These items were drawn from the Australian Household Expenditure Survey (Australian Bureau of Statistics, 2002).
Krause N,	2009	Chronic Financial Strain. Measured with three items from Pearlin et al., 1981: 1. How much difficulty do you have meeting the monthly payments on your bills? 2. In general, how would you say your finances usually work out at the end of the month? 3. How would you rate your financial situation these days?
Huddleston-Casas C, Charnigo R, Simmons L	2009	Food insecurity. Measured using the Core Food Security Module (CFSM), an eighteen-item scale with a 12-month time reference.
Chiao C, Weng L, Botticello A	2009	Financial hardship. Assessed by asking older adults whether they had enough living expenses, or experienced a shortage of living expenses.
Heflin C, Iceland J	2009	Financial hardship. Assessed across domains: 1. Food insecurity; 2. Difficulty paying bills; 3. Lack of medical care; 4. Telephone turned off; 5. Unstable housing. - Food insecurity assessed with the question: "In the past 12 months, did you receive free food or meals?". - Difficulty paying bills assessed by asking whether a respondent did not pay the full amount of rent or mortgage, the full amount of a gas, oil or electricity bill, or whether they had to borrow money from friends or family to help pay bills. Respondents were classified as having difficulty paying bills if they affirmed any of these three items. - Lack of medical care assessed with the question: "In the past 12 months, was there anyone in your household who needed to see a doctor or go to the hospital but couldn't go because of the cost?". - Telephone turned off was assessed with the question: "In past year, was telephone service ever disconnected?". - Unstable housing was assessed by asking respondents if they were: 1. Evicted for nonpayment; 2. Stayed at a shelter, in an abandoned building, an automobile, or any other place not meant for regular housing even for one night; 3. Moved in with other people even for a little while because of financial problems. (An affirmative answer to any of these three items classified a respondent as experiencing unstable housing).
Xiaowan Lin, Leung K	2010	Economic hardship. Measured with the question: "How do you evaluate the financial situation of you and your family if you cannot find a job in a short time and continue to receive assistance from the Comprehensive Social Security Assistance (CSSA) Scheme". (1 = extremely bad; 5 = extremely good).
Wang J, Schmitz N, Dewa C	2010	Financial Strain. Assessed with the question "You don't have enough money to buy the things you need" ('True' / 'False').
Burdette A, Hill T, Hale L	2011	Financial Hardship. Measured as the mean response to 13 items. Respondents were asked to indicate how often they had to "borrow money to pay bills." Respondents were also asked to indicate whether they had enough money to "afford housing, food, and clothing" and whether any adults or children in the household were "unable to eat for a whole day because there wasn't enough money for food."
Howden-Chapman P, Chandola T, Stafford M, Marmot M	2011	Household financial problems. Measured with the question: "To what extent do you have difficulty paying bills"; ("very great problems" to "very little").
Sargent-Cox K, Butterworth P, Anstey K	2011	Financial Hardship. Assessed with the question: "Over the last year, have you: 1. Pawned or sold something; 2. Gone without meals; 3. Been unable to heat your home; 4. Requested assistance from welfare or community organizations (yes/no) due to money shortage?"
Cole S, Tembo G	2011	Household food insecurity. Assessed using a modified 7-item scale proposed by Maxwell (1996). The scale was constructed using a number of focus group discussions to identify local coping strategies used in times of food insecurity. The following were identified as the seven most common strategies: 1. Consuming relish (a side dish, i.e., pumpkin leaves) without nsima (the staple food); 2). Borrowing money or food from relatives or friends; 3. Selling/trading livestock or personal items to get more food; 4. Doing ganyu (piecework) for food or money to buy/get food; 5. Gathering wild foods or cooking bananas to eat in place of nsima; 6. Going to sleep hungry; and 7. Sitting the entire day without food. Household heads were asked if they employed each strategy "never," "some days," "many days," or "every day" over the course of the rainy or the dry season. Scoring ranged from 0 if a household head responded "never" to 3 if they responded "every day."
Manuel J, Martinson M, Bledsoe-Mansori S, Bellamy J	2012	Economic and Material Hardship. Assessed using 7 items. "In the past 12 months, did you: 1. Receive free food/meals? 2. Not pay full amount of rent/mortgage? 3. Get evicted for not paying rent/mortgage? 4. Not pay full gas/ oil/electricity bill? 5. Have gas/oil/electricity shut off or withheld? 6. Have the telephone service disconnected for non-payment? 7. Have anyone in the house need to see a doctor or go to the hospital but couldn't go because of cost?" Items were summed to create an index ranging from 0 (no hardships) to 7 (all seven hardships) and then collapsed into three categories: no hardship, moderate hardship (1 hardship), and severe hardship (2 or more).
Frank C, Davis C, Elgar F	2014	Financial Strain. Measured using two items from Pearlin et al. (1981). Respondents were asked to what extent they have had difficulty paying bills in the past 12 months (1 = a great deal of difficulty; 5 = no difficulty at all) and the extent to which they have enough money left at the end of the month (1 = more than enough money left over; 5 = not enough to make ends meet).
Mckenzie S, Imlach Gunasekara F, Richardson K, Carter K	2014	Individual Deprivation. Measured using the NZ Individual Deprivation Index (NZiDep). Produces a composite score from eight items reflecting limitations in consumption, such as being forced to buy cheaper food, feeling cold to save on heating costs, wearing worn-out shoes, or receiving help from community organisations. Scored from 0 (no hardship) to 8 (greatest hardship).
Chen Y, Chiao C, Ksobiech K	2014	Economic strain. Assessed by asking whether respondents had enough money for living expenses, or had experienced a shortage. Responses were categorized as "experienced economic strain" or "have not experienced economic strain".
Maclean J, Webber D, French M	2014	Perceived Financial Strain. Measured by asking respondents whether they had experienced "a major financial crisis, declaring bankruptcy, or more than once unable to pay bills on time".

Drentea P, Reynolds J	2015	Economic Hardship. Measured using a four-item scale: "When you think of your financial situation overall, how difficult is it for you to meet the following needs?" 1. Housing, 2. Food, 3. Transportation, and 4. Medical expenses. Response options of, not at all difficult (coded 0), somewhat difficult (1), and very difficult (2). Answers to the four items averaged.
Kiely K, Leach L, Olesen S, Butterworth P	2015	Financial Hardship. Assessed by asking respondents if the following events had occurred in the current year due to a shortage of money: 1. Could not pay electricity, gas or telephone bills on time; 2. Asked for financial help from friends or family; 3. Could not pay mortgage or rent on time; 4. Pawned or sold something; 5. Was unable to heat home; 6. Went without meals; 7. Asked for help from welfare/community organisations.
Maclean J, Webber D, French M, Ettner S	2015	Perceived Financial Strain. Measured by asking respondents whether they had 1. Experienced a major financial crisis; 2. Declared bankruptcy; 3. Were more than once unable to pay bills on time.
Dijkstra-Kersten S, Biesheuvel-Leliefeld K, Van Der Wouden J, Penninx B, Van Marwijk H	2015	Financial Strain. Measured by asking "In general: How is your financial status at the end of each month?". 'Usually money left' (no financial strain), 'Just enough money to manage' (mild financial strain), 'Not enough money to manage' (severe financial strain).
Holden L, Ware R, Lee C	2016	Financial Circumstances. Assessed by asking respondents about their ability to manage on available income. Five response options, grouped into three categories for analysis: 1. no difficulty, 2. difficult some of the time, and 3. impossible/difficult all the time.
Crowe L, Butterworth P	2016	Financial Hardship. Assessed using four items from the Australian Household Expenditure Survey. "Over the past year have the following happened to you because you were short of money": 1. pawned or sold something; 2. Went without meals; 3. Unable to heat home; 4. Asked for help from welfare/community organisations. Participants endorsing one or more of these items were categorised as experiencing financial strain. In Wave 1, a measure of financial difficulty was used which asked participants if they had gone without things they really needed in the last year because they were short of money. Participants who answered 'yes, sometimes 'and 'yes often' were categorised as experiencing financial strain.
Landstedt E, Coffey J, Wyn J, Cuervo H, Woodman D	2016	Financial hardship. Measured according to answers to the following: 1. I have trouble affording my accommodation; 2. After I have paid for my accommodation there is little left for other necessities; 3. I need to economize on food; 4. I am not able to afford to socialize with friends; 5. I am not able to maintain my health and well-being (e.g., healthcare and exercise); 6. I am not able to afford transport. Response alternatives were never, occasionally, often. Each item was dichotomized into no hardship (never) and yes hardship (occasionally and often). These dichotomous variables were summarized into a composite measure (with range 0–6).
Nam I,	2016	Financial difficulty. Assessed using the item "How hard is it for you to pay for basic necessities such as food, housing, medical care, and heating?" Rated on a four-point Likert-type scale ranging from "not difficult at all" (0) to "very difficult" (3).
Curl A, Kearns A	2016	Fuel affordability. Survey respondents asked how often they have difficulty affording essential items, including fuel bills. Four response categories: Never; Occasionally; Quite Often; Very Often.
Crowe L, Butterworth P, Leach L	2016	Financial Hardship. Assessed by asking respondents if the following events had occurred in the current year due to a shortage of money: 1. Could not pay electricity, gas or telephone bills on time; 2. Asked for financial help from friends or family; 3. Could not pay mortgage or rent on time; 4. Pawned or sold something; 5. Was unable to heat home; 6. Went without meals; 7. Asked for help from welfare/community organisations.
Barthel D, Kriston L, Fordjour D, Mohammed Y, Kra-Yao E, Bony Kotchi C, Koffi Armel E, Eberhardt K, Feldt T, Hinz R	2017	Economic Stress. Assessed by asking respondents to affirm the following: 1. Having too little money; 2. Being in serious debt; 3. Having to support family in financial need.
Richardson T, Elliott P, Roberts R, Jansen M	2017	Index of Financial Stress (IFS) (Siahpush and Carlin, 2006). Measured financial difficulties/stress over the past 6 months via questions such as 'Could not pay the mortgage or rent on time'. Note, This measure contains more or less identical items to the 7 items comprising the ABS Household Expenditure Survey (HES) measure, and adds an additional eighth item that asks whether they could raise AUD $2000 in a week.
French D,	2017	Household financial situation: Assessed from responses to the question 'How well would you say you yourself are managing financially these days?': 1. 'living comfortably'; 2. 'doing alright'; 3. 'just about getting by'; 4. 'finding it quite difficult'; 5. 'finding it very difficult'. Financial strain defined as the head of household responding that they are 'finding it quite difficult' or 'finding it very difficult'.
Russell D.W., Clavel F.D., Cutrona C.E., Abraham W.T., Burzette R.G.	2018	Financial Strain. Assessed chronic and acute financial problems using a set of 32 items developed by Conger and Elder (1994).
Mccarthy B, Carter A, Jansson M, Benoit C, Finnigan R	2018	Material Hardship. Measured using a three-item scale. I.e., the average frequency (1 = never or rarely, 2 = sometimes, 3 = often or almost always) of the following during the 4 months prior to each interview: (i) having problems paying for basic necessities, (ii) not having enough food because of a lack of money, and (iii) not having the quality or variety of food desired because of a lack of money.
Darin-Mattsson A, Andel R, Celeste R, Kåreholt I	2018	Financial Hardship: Assessed with respect to the following: "If a situation suddenly arise where you need to raise X SEK in a week, would you be able to?". In 1968, the amount was set at 2000 SEK; thereafter it was adjusted to have the same purchase value at each wave of interviews as 2000 SEK had in 1968. The amount of 2000 SEK in 1968 corresponded to 15,000 SEK in 2011. Response alternatives were "no", "yes – by bank loan, help from friends or relatives", or "yes – by myself or with help from family". "No" was considered severe financial hardship, "yes – by bank loan, help from friends or relatives" was considered as slight financial hardship and "yes – by myself or with help from family" was considered no financial hardship.

Koltai J, Bierman A, Schieman S	2018	Subjective Financial Strain. Assessed using three items. "During the last year, how often did you: Have trouble paying the bills? and how often did you not have enough money to buy food, clothes or other things your household needed?" Answers were coded as 1. "Never", 2. "Rarely", 3. "Sometimes", 4. "Often", 5. "Very often". Respondents were also asked: "How do your finances usually work out by the end of the month?" Responses to this question were coded 1. "A lot of money left over", 2. "A little money left over", 3. "Just enough to make ends meet", 4. "Not enough to make ends meet".
Kim Y, Park A, Kim K	2018	Food Insecurity. Measured using 6 questions adapted from the United States Department of Agriculture's (USDA) Food Security Scale (Bicket et al., 2000), which investigates whether a household experienced food hardships in the past year as a result of economic difficulties. The questions are: 1. 'The food that (I/we) bought just did not last, and (I/ we) did not have money to get more'; 2. '(I/We) could not afford to eat balanced meals'; 3. 'In the last 12 months, did (you/other adults in your household) ever cut the size of your meals or skip meals because there was not enough money for food?'; 4. (If yes in the previous question) 'how often did this happen?'; 5. 'In the last 12 months, did you ever eat less than you felt you should because there was not enough money to buy food?'; 6. 'In the last 12 months, were you ever hungry but did not eat because you could not afford enough food?'
Austin E, Handley T, Kiem A, Rich J, Lewin T, Askland H, Askarimarnani S, Perkins D, Kelly B	2018	Financial security. Respondents rated whether they were 'Prosperous/very comfortable', 'Reasonably comfortable', or 'Just getting along/poor/very poor'.
Wu Q, Harwood R, Feng X	2018	Food insecurity. Assessed using the USDA Household Food Security Survey Module (Bickel et al., 2000).
Butterworth P, Kelly B, Handley T, Inder K, Lewin T	2018	Financial Hardship. Assessed by asking respondents if the following events had occurred in the current year due to a shortage of money: 1. Could not pay electricity, gas or telephone bills on time; 2. Asked for financial help from friends or family; 3. Could not pay mortgage or rent on time; 4. Pawned or sold something; 5. Was unable to heat home; 6. Went without meals; 7. Asked for help from welfare/community organisations.
Winzer R, Sorjonen K, Lindberg L	2018	Economic Strain. Assessed with two questions. Question 1: "has it happened during the past 12 months that you had to borrow money from relatives or friends to manage current expenditures for food and rent?" 1. No; 2. Yes, once; 3. Yes, several times. Question 2: "Have you, in the past 12 months refrained from going to the dentist, medical services or picking up prescriptions as a result of poor finances?" 1. No; 2. Yes, the dentist due to poor finances; 3. Yes, medical services due to poor finances; 4. Yes, picking up prescriptions due to poor finances.
Cooper S, Enticott J, Shawyer F, Meadows G	2019	Financial Hardship. Assessed by asking respondents if the following events had occurred in the current year due to a shortage of money: 1. Could not pay gas, electricity or telephone bills on time; 2. Could not pay the rent or mortgages on time; 3. Went without meals; 4. Were unable to heat or cool your home; 5. Pawned or sold something because you needed cash; 6. Needed help from a welfare or community organisation.
Handley T, Rich J, Lewin T, Kelly B	2019	Perceived Financial Status. Measured by a single item taken from the Household, Income and Labour Dynamics in Australia (HILDA) survey: "Given your current needs and financial responsibilities, would you say that you and your family are: 1. Prosperous; 2. Very comfortable; 3. Reasonably comfortable; 4. Just getting along; 5. Poor; 6. Very poor?"
Whitsett D, Sherman M, Kotchick B	2019	Food insecurity. Assessed using the USDA Household Food Security Survey Module (Bickel et al., 2000).
Forbes M, Krueger R	2019	Financial Impacts. Assessed with a Yes/No to the following questions: 1. Declared bankruptcy; 2. Missed a credit card payment; 3. Missed other debt payments, car/student loans; 4. Increased credit card debt; 5. Sold possessions to make ends meet; 6. Cut back on your spending; 7. Exhausted unemployment benefits.
Steptoe A, Emch S, Hamer M	2020	Financial Strain. Assessed using 8 items. Each rated on a 3-point scale (1 = no difficulty, 2 = some difficulty, 3 = very great difficulty). Items were as follows; 1. "Are you able to afford furniture or household equipment that needs to be replaced?"; 2. "Do you have enough money for the kind of food you and your family should have?": 3. "Do you have problems in paying your bills?"; 4. "Do you have enough money for the kind of clothing you and your family should have?"; 5. "Are you able to afford to replace major items (such as a car) when you need to?"; 6. "Do you have enough money for the leisure activities you and your family want?"; 7. "Are you able to afford a home suitable for you and your family?"; 8. * *Eighth item not disclosed in text (author confirmed via email that 8 items were indeed assessed).*
Hashmi R, Alam K, Gow J	2020	Financial Hardship. Assessed by asking respondents if the following events had occurred in the current year due to a shortage of money: 1. Could not pay electricity, gas or telephone bills on time; 2. Asked for financial help from friends or family; 3. Could not pay mortgage or rent on time; 4. Pawned or sold something; 5. Was unable to heat home; 6. Went without meals; 7. Asked for help from welfare/community organisations.
Torlinska J, Albani V, Brown H	2020	Financial Hardship. Assessed according to responses to the following questions: 1. Inability to pay the bills on time; 2. Inability to pay the rent or mortgage on time; 3. Going without meals; 4. Inability to heat/cool the home; 5. Pawning or selling something for cash; 6. Needing help from welfare or charity.
Stepanikova I, Acharya S, Abdalla S, Baker E, Klanova J, Darmstadt G	2020	Financial Hardship. Respondents rated how difficult it was to provide food, clothing, heating, and rent/mortgage payments for their family. Also rated how difficult it was to provide things for their child. Each item was rated on a four-point scale (0 = "Not difficult" to 3 = "Very difficult"). Mean of the four items was calculated to represent overall financial hardship.
Chung R, Marmot M, Mak J, Gordon D, Chan D, Chung G, Wong H, Wong S	2020	Deprivation. Assessed using 21 items - 4 were measures of social deprivation; 17 were measures of material deprivation, including 'food deprivation' (3 items), 'clothing deprivation' (3 items), 'medical care deprivation' (3 items), 'household facilities and equipment' (5 items), 'repair and maintenance' (2 items) and 'finance' (1 item). Respondents affirming two or more items were categorised as deprived.
Klug K, Selenko E, Gerlitz J	2020	Perceived financial strain. Measured with a single item asking respondents how much they worry about their personal economic situation on a three-point scale; 1. Very worried, 2. Somewhat worried, 3. Not worried at all.
Lyu S, Sun J	2020	Financial hardship. Assessed with a measure of personal relative deprivation. Respondents were asked "how do you rate your economic status compared with other local people?" Answers ranged from 1 to 5 - a higher score indicated greater subjective feelings of personal relative deprivation.

Amegbor P, Kuuire V, Yawson A, Rosenberg M, Sabel C, Aboderin I	2021	Social frailty. Measured using five items: social isolation, financial need, food insecurity (eating less and going hungry or not eating), and physical need. Social isolation was measured using an index created from three questions in the WHO-SAGE wave 2 that asked respondents if a) they lacked companionship b) felt left out and c) felt isolated. The questions had the following ordinal responses: never, rarely, sometimes, and often. The index ranged from 3 to 12 with higher scores indicating elevated social isolation. Financial need was an ordinal variable constructed from the SAGE question – "Do you have enough money to meet your needs?". Respondents could answer "completely", "mostly", "moderately", "a little" and "none at all". The survey had two questions on food insecurity: a) "In the last 12 months, how often did you ever eat less than you felt you should because there wasn't enough food?" and "In the last 12 months, were you ever hungry, but didn't eat because you couldn't afford enough food?". Both questions had the following responses: "every month," "almost every month," "some months, but not every month," "only 1 or 2 months," and "never."
Wright L., Steptoe A., Fancourt D.	2021	Adversities. Assessed by asking respondents whether they were 1. Unable to access sufficient food; 2. Unable to access required medication.
Cao H, Zhou N, Li X, Serido J, Shim S	2021	Financial Stress. Three items used to measure the extent participants were constantly worried about money; have difficulties paying for things; and feel satisfied with their current financial status. Responses rated on a 5-point scale (1 = strongly disagree; 5 = strongly agree).
Bierman A, Upenieks L, Glavin P, Schieman S	2021	Economic hardship. Measured using three questions adapted from Kahn and Pearlin (2006) and Mirowsky & Ross (1999). 1. "How often in the past month did you have trouble paying the bills?"; 2. "How often in the past month did you not have enough money to buy food, clothes or other things your household needed?"; 3. How did your finances work out in the past month?".
Porter C, Favara M, Hittmeyer A, Scott D, Sánchez Jiménez A, Ellanki R, Woldehanna T, Duc L, Craske M, Stein A	2021	Food insecurity. Assessed by asking respondents whether they had reduced food consumption due to adverse economic events
Lee T, Kuo J, Liu C, Yu Y, Strong C, Lin C, Lee C, Tsai M	2021	Food Insecurity. Measured using four items: 1. Eating less than three meals and no other snacks in a day; 2. Starving due to a lack of money; 3. Skipping breakfast or lunch in order to save money; 4. Financial difficulties in paying for lunch. This measure referenced the original Core Food Security Module developed by the US Department of Agriculture.
Batterham P, Calear A, Mccallum S, Morse A, Banfield M, Farrer L, Gulliver A, Cherbuin N, Rodney Harris R, Shou Y	2021	Perceived Hardship. Assessed with the question, "Over the past 2 weeks, to what extent have you experienced financial distress related to COVID-19?".
Pierce M, Mcmanus S, Hope H, Hotopf M, Ford T, Hatch S, John A, Kontopantelis E, Webb R, Wessely S	2021	Problems Paying Bills. Assessed using a binary variable to indicate whether participants had problems with paying bills during the pandemic.
Bialowolski P, Weziak-Bialowolska D, Lee M, Chen Y, Vanderweele T, Mcneely E	2021	Financial distress. Assessed using two questions. 1. "The amount of debt I have often overwhelms me" (0 = Strongly disagree, 10 = Strongly agree); 2. "How often do you worry about food, housing, or health expenses?" (0 = Do not ever worry, 10 = Worry all of the time). Measure modified from work by VanderWeele et al., 2019.
Kang S, Kim S, Park E, Jang S	2021	Material Hardship. Assessed using 13 questions inquiring whether specific deprivations had occurred in the preceding 12 months. These included: 1. Ran out of food and could not afford to buy more; 2. Could not afford balanced meals; 3. Adults in the household skipped meals or did not have enough to eat; 4. Ate less than needed because could not afford to buy enough food; 5. Were hungry but did not eat because could not afford to buy food to eat; 6. Had electricity, telephone, or water disconnected because of unpaid bills; 7. Unable to pay utility bills before the due date; 8. Unable to pay rent for over two months or had to move out because of unpaid rent or inability to pay rent; 9. Unable to sufficiently heat the home during the winter; 10. Myself or other family members needed to see a doctor but could not afford to go; 11. Unable to pay the national health insurance premium and lost eligibility for national health insurance; 12. Had problems with credit; 13. Unable to pay children's public education tuition. If participants answered 'Yes' to at least one of the 13 questions, they were classified as having experienced Material Hardship.
Preetz R, Filser A, Brömmelhaus A, Baalmann T, Feldhaus M	2021	Financial Strain. Measured with the question, "How strained are you by your current financial situation?" (1 = not at all; 5 = very much). Within-person change scores were calculated between June 2020 and each respondents' most recent previous response. Positive scores indicated an increase in the participants' strain compared to their previous response.
Lee E, Man R, Gan T, Fenwick E, Aravindhan A, Ho K, Sung S, Wong T, Ho C, Gupta P	2021	Financial Impact. Measured using a 12-item scale, designed to examine the financial impact of COVID lockdown on participants. Participants described their household's financial position during the lockdown from 0 (no problems) to 2 (major problems). Participants also indicated how their household income had changed during lockdown from 1 (increased a lot) to 5 (decreased a lot). Eight items also assessed changes in lifestyle in the participants' household due to the financial constraints associated with the lockdown.
Dickerson J., Kelly B., Lockyer B., Bridges S., Cartwright C., Willan K., Shire K., Crossley K., Bryant M., Siddiqi N.	2022	Financial hardship. Assessed with a general measure of financial security. Response options included: 1. 'Living comfortably'; 2. 'Doing alright'; 3. 'Just about getting by'; 4. 'Finding it quite/very difficult'.
Sommet N, Spini D	2022	Financial Scarcity. Participants reported whether their household, 1. "Saves money"; 2. "Spends what it earns"; 3. "Taps into its assets and savings"; 4. "Acquires debt".
Finnbogadóttir H, Persson E	2022	Financial Difficulties. Unclear how this was measured.
Haag K, Du Toit S, Skeen S, Steventon Roberts K, Chideya Y, Notholi V, Sambudla	2022	Household Food Insecurity. Measured from 0–27, using the Household Food Insecurity Access Scale (HFIAS) (Coates et al., 2007).

A, Gordon S, Sherr L, Tomlinson M		
Marshall G.L., Ingraham B., Major J., Kahana E., Stansbury K.	2022	Financial Hardship. Assessed using two indicators: 1. Difficulty paying bills and; 2. Reduced medication use due to cost. Difficulty paying bills was measured using the following question: "How difficult is it for you/your family to meet monthly payments on your/your family's bills?" (1 = Not at all difficult; 5 = Completely difficult). Reduced medication use due to cost was measured by asking, "Have you ended up taking less medication than was prescribed for you because of cost?" (Yes / No).
Mohan G,	2022	Household Energy Poverty; Household Behind on Utility Bills. Assessed by asking the primary caregiver 'Does the household keep the home adequately warm?' (1 = No, cannot afford; 2 = No, cannot other; 3 = Yes). The 'No, cannot afford' responses were used to construct a variable that represents households which could not afford to adequately heat their homes - categorized as 'cold home'. Another question asked 'Have you ever had to go without heating during the last 12 months through lack of money? (I mean have you had to go without a fire on a cold day, or go to bed to keep warm or light the fire late because of lack of coal/fuel?)' (Yes / No). 'Yes' responses were categorised as 'gone without heat'. Energy poverty was defined as having either a 'cold home' and/or 'gone without heat'.
Shepherd D,	2022	Food Insecurity. Respondents were asked whether their household had run out of money to buy food in the previous month, and whether anyone in their household had gone hungry in the last 7 days because there wasn't enough food. The latter question was proceeded by an assessment of hunger occurrence on a 5-point Likert scale of 0 = never; 1 = 1 or 2 days; 2 = 3 or 4 days; 3 = almost every day; 4 = every day.
Cho J,	2022	Food insecurity. Measured with two items from the 6-item short-form K-HFSSM (Household Food Security Survey Module). Variables included 'having an experience of not being able to buy any food due to financial difficulties' and 'having an experience of not being able to eat enough due to financial difficulties'.
Porter C, Hittmeyer A, Favara M, Scott D, Sánchez A	2022	Food Insecurity. Assessed according to whether the participants household reported running out of food at least once since the beginning of the COVID pandemic.
Zhang X, Zhang Y, Vasilenko S	2022	Material hardship. Measured using eight dichotomous questions about financial difficulties experienced in the past year(s). Yes responses were summed to create an index - higher scores indicated higher levels of material hardship.
Moreno-Agostino D, Fisher H, Hatch S, Morgan C, Ploubidis G, Das-Munshi J	2022	Assessed by asking respondents to report (retrospectively) their self-reported financial situation in the three months prior to the pandemic outbreak. Response options comprised: 1. 'Living comfortably'; 2. 'Doing all right'; 3. 'Just about getting by'; 4. 'Finding it quite difficult'; 5. 'Finding it very difficult'.
Hecker I, El Aarbaoui T, Wallez S, Andersen A, Ayuso-Mateos J, Bryant R, Corrao G, Mcdaid D, Mediavilla R, Mittendorfer-Rutz E	2022	Financial Difficulties during COVID-19. Assessed by asking about participants' financial difficulties in the preceding 7 days (or since the last assessment), across four domains: 1. "Paying the rent, heat or electricity bills for your home"; 2. "Paying for medical care or medication (for you, your partner or your children)"; 3. "Eating in sufficient quantities (you had to reduce your size or frequency of meals)"; 4. "Eating varied and balanced meals (you had to eat the same thing several times)". If participants affirmed at least one item they were classified as having financial difficulties
Stein G, Jensen M, Christophe N, Cruz R, Martin Romero M, Robins R	2022	Adolescent perceptions of economic hardship. Computed as a mean of 12 items. Based on work by Conger et al., (1991). Adolescents reported their level of agreement to the 12 items on a 5-point Likert type scale. For example, two items were "Because you do not have much money, your family has a hard time paying bills" and "You often worry about your family's poor financial situation."
Tancredi S., Wagner C., Keidel D., Witzig M., Imboden M., Probst-Hensch N., Amati R., Albanese E., Levati S., Crivelli L.	2023	Financial Resources. Assessed by asking participants, "In the past 6 months, would you say that financially..." 1. "You are comfortable, money is not a concern and it is easy to save money"; 2. "Your income allows you to cover your expenses and to compensate for any minor contingencies"; 3. "You need to be careful with your expenses and an unforeseen event could put you in financial difficulty"; 4. "You are unable to cover your needs with your income and need external support to function (debt, credit, various financial aids)".
Bentley R., Daniel L., Li Y., Baker E., Li A.	2023	Energy Poverty. Assessed by asking respondents whether they were unable to heat their home because of a shortage of money (Yes / No).
Choi M, Lee E, Sempungu J, Lee Y	2023	Financial Hardship. Assessed by asking household heads whether they experienced the following seven items due to financial difficulties in the previous year: 1. "having trouble paying rent or evicted for not paying rent"; 2. "having trouble paying utility bills"; 3. "having trouble heating the home in winter"; 4. "having problems receiving medical services"; 5. "family with bad credit"; 6. "having problems paying national health insurance premium"; 7. "having problems eating nutritious food."
Moulton V, Sullivan A, Goodman A, Parsons S, Ploubidis G	2023	Change in financial situation. Assessed with the question: "Overall how do you feel your current financial situation compares to before the coronavirus outbreak?". 1. Much worse off; 2. A little worse off; 3. About the same; 4. A little/much better off.

Appendix A.9

No. of financial hardship measures by 'type' and method of implementation.

FH Measure - Type	FH Measure - Implementation	n
Not stated	Not stated	2
Perceived deprivation/general finances	Not stated	1
Perceived deprivation/general finances	(Multi-item) Scale	4
Perceived deprivation/general finances	General financial question(s)	25
Specific deprivations experienced	(Multi-item) Scale	45
Specific deprivations experienced	(Individual) Item(s)	17

Appendix A.10

No. of items used, and distinct hardship domains assessed within multi-item or individual item measures of financial hardship.

Characteristic	Individual item(s)	Multi-item
FH - No. of Items		
1	11	
2	3	5
3	1	9
4		8
5	1	2
6		4
7	1	7
8		5
9		1
10		1
12		1
13		2
18		2
21		1
32		1
FH - No. of Domains Assessed		
1	13	9
2	2	4
3		4
4		7
5	1	2
6		3
7	1	6
8		5
10		1

Appendix A.11

Analytic techniques/strategies used within included studies.

Analytic Technique / Strategy	Analytic/Strategy Group	n
ANCOVA	Other	1
Auto-Regressive Cross-Lagged Panel Modelling	Regression	1
Cochrane's Q-test	Other	1
Complementary Log-Log Regression	Regression	1
Confirmatory Latent-Variable Structural Modelling (SEM)	SEM	1
Correlation analysis	Correlation	1
Cox Proportional-Hazards Regression Model	Regression	1
Cross-Lagged Dynamic Panel Models	Regression	1
Cross-lagged Panel Model (CLPM); Latent Growth Curve Modelling; Random Intercept, Cross-Lagged Panel Model (RI-CLPM)	Regression; Growth Curve Models	1
Fixed Effects Regression	Regression	7
Fixed Effects Regression; Correlated Random Effects Regression	Regression	1
Fixed Effects Regression; Random Effects Regression	Regression	1
Fixed-Effects Linear Panel Modelling	Regression	1
Generalised Estimating Equations (GEE) (Regression)	Regression	5
Generalised Estimating Equations (GEE) (Regression); Group Based Trajectory Modelling (GBTM)	Regression; Growth Curve Models	1
Generalised Estimating Equations (GEE) (Regression); Multivariate Linear Regression	Regression	1
Generalised Least Squares Regression (GLS)	Regression	1
Generalised Linear Mixed Model (GLMM) Regression	Regression	1
Generalised Linear Mixed Model (GLMM) Regression; Time-Lagged Generalised Linear Mixed Models (GLMM)	Regression	1
Hierarchical Linear Modelling (HLM) Regression	Regression	1
Hierarchical Ordinary Least Squares (OLS) Multiple Regression	Regression	1
Hierarchical Regression	Regression	2
Latent Change Score Modelling	Other	1
Latent Growth Curve Modelling; Parallel Process Latent Growth Curve Modelling	Growth Curve Models	1
Linear General Estimating Equations (L-GEE) (Regression)	Regression	1
Linear Mixed Error-Component (Panel) Models	Regression	1
Linear Regression	Regression	2
Logistic Regression	Regression	10
Logistic Regression; Linear Regression	Regression	3
Logistic Regression; Mundlak Method	Regression	1
Mixed-Effects Linear Regression	Regression	1
Multilevel Growth Curve modelling	Growth Curve Models	3
Multilevel Logistic Regression	Regression	2

Multilevel Mixed Effects Logistic Regression	Regression	1
Multilevel Regression	Regression	2
Multinomial Logistic Regression; Group Based Trajectory Modelling (GBTM)	Regression; Growth Curve Models	1
Multinomial Logistic Regression; Growth Mixture Modelling	Regression; Growth Curve Models	1
Multinomial Logistic Regression; Poisson Regression	Regression	1
Multinomial Logistic Regression; Quadratic Growth Models; Quadratic Growth Mixture Models	Regression; Growth Curve Models	1
Multivariable Linear Regression; Multivariable Logistic Regression	Regression	1
Multivariable Logistic Regression	Regression	2
Multivariate Linear Regression	Regression	1
Oaxaca-Blinder type decomposition	Other	1
Ordinary Least Squares Regression (OLS)	Regression	5
Panel Logistic Regression	Regression	1
Path Analysis (SEM)	SEM	1
Poisson Regression	Regression	1
Propensity Score Analysis (PSA)	Other	1
Random-Effects Probit Regression Models	Regression	1
Repeated Measures Multiple Regression; Nested Multivariate Models	Regression	1
Structural Equation Modelling (SEM)	SEM	8
Structural Equation Modelling (SEM); Growth Curve Analyses	SEM; Growth Curve Models	1
Structural Equation Modelling (SEM); Multilevel Regression	SEM; Regression	1
t-test	Other	1

Appendix A.12

Number of statistical techniques used by analytic family.

Analytic Technique / Strategy (Group)	n
Correlation	1
Growth Curve Models	10
Regression	72
SEM	12
Other	6

Appendix A.13

All confounders/controls within included studies

Control - Items	Control - Groups	n
Access to house amenities (at 7/5)	SES - Housing	1
Adverse life events (number experienced)	Adversities	2
Affected by bushfire smoke	Adversities	1
Affected by other adversity	Adversities	1
Age	Demographics	51
Age (at baseline)	Demographics	2
Age (caregiver)	Demographics	1
Age (child)	Demographics	1
Age (when gave birth to child)	Demographics	1
Age group	Demographics	10
Age of youngest child in house	Demographics	2
Age squared	Demographics	1
Alcohol consumption	Alcohol/Smoking/Drug use	7
Anxiety symptoms	Mental Health	1
Any HIV in family	Family factors	1
Any medical conditions (at 7/5)	Physical Health	1
Area-Level Disadvantage	Neighbourhood factors	4
Asked by UK NHS to 'shield' due to pre-existing physical illness	Physical Health	1
Assessment cycle	Study Methodology/Factors	1
Assets	SES - Income/Wealth	1
Attrition	Study Methodology/Factors	1
Baseline CESD	Mental Health	1
Baseline CIS-R score	Mental Health	1
Baseline mental health	Mental Health	1
Baseline psychological distress	Mental Health	1
Baseline self-rated health	Physical Health	1
Baseline SF-36 Mental Health	Mental Health	1
Birth weight	Other	1
BMI (at 11/10)	Physical Health	1
Body mass index (BMI)	Physical Health	1
Building type	SES - Housing	1
Caregiver depression	Family factors	1
Change in occupation	SES - Employment & Labour Market Characteristics	2
Change in social integration (Social Integration Scale)	Other	1
Change in strain due to uncertain job market prospects	SES - Employment & Labour Market Characteristics	1
Change in workload	SES - Employment & Labour Market Characteristics	1
Changes in household income	SES - Income/Wealth	1
Childhood abuse	Adversities	1
Childhood economic conditions	SES - Childhood	1
Childhood poverty	SES - Childhood	1
Chronic kidney disease	Physical Health	1
Church attendance	Other	1
City of residence	Demographics	1
Club/community activities	Other	1
CM wet the bed (at 7/5)	Other	1
Cognitive ability (at 7/5 and 11/10)	Other	1
Cognitive problems	Mental Health	1
Cohabiting	Relationship	1
Cohort	Study Methodology/Factors	1
Community cohesion	Neighbourhood factors	1
Community disorder	Neighbourhood factors	1
Community racism	Neighbourhood factors	1

Community work	Neighbourhood factors	1
Community/civic engagement	Other	1
Community-level capital	Neighbourhood factors	1
Concerns about rural community	Neighbourhood factors	1
Considered abandoning studies due to finances	SES - Income/Wealth	1
Considered not coming to university due to finances	SES - Income/Wealth	1
Country	Demographics	2
Country of birth	Demographics	1
Country of origin (UK/Non-UK)	Demographics	1
COVID related worries	COVID-19	1
COVID vaccination status	COVID-19	1
COVID-19 exposure	COVID-19	1
COVID-19 infection status	COVID-19	1
COVID-19 like symptoms	COVID-19	1
COVID-19 related impairment	COVID-19	1
Crowding (at age 0, 7/5 and 11/10)	SES - Housing	1
Current smoking status	Alcohol/Smoking/Drug use	3
Daily hours spent looking after children (0-16 hours)	Family factors	1
Day of the week	Study Methodology/Factors	1
Debt stress	SES - Income/Wealth	1
Dependency ratio (proportion of people living in the household less than 15 and greater than 59 years of age)	Family factors	1
Dependent children (yes/no)	Family factors	1
Depression (current wave)	Mental Health	1
Depressive symptoms (4 years prior)	Mental Health	1
Depressive symptoms at time point 1 (Wave 5)	Mental Health	1
Disability status	Physical Health	4
Domestic violence	Adversities	3
Drought condition (rainfall previous 12 months)	Adversities	1
Drug use (socially acceptable)	Alcohol/Smoking/Drug use	1
Drug use (socially unacceptable)	Alcohol/Smoking/Drug use	1
Education (caregiver)	SES - Education	1
Education (completed or not completed year 12)	SES - Education	4
Education (highest grade of school or college completed)	SES - Education	1
Education (highest level attained)	SES - Education	38
Education (more or less than 12 years)	SES - Education	1
Education (more or less than 13 years)	SES - Education	1
Education (years)	SES - Education	6
Education level (high/low)	SES - Education	1
Emotional detachment from unemployment (distancing)	Other	1
Emotional support	Other	1
Emotional/Physical neglect (during childhood)	Adversities	1
Employment history (proportion of time in employment since first leaving full-time study)	SES - Employment & Labour Market Characteristics	1
Employment status	SES - Employment & Labour Market Characteristics	32
English language ability	Demographics	1
EPQN (neuroticism subscale)	Personality	2
Ethnic discrimination	Adversities	2
Ethnicity/Race	Demographics	20
Ethnicity/Race (caregiver)	Demographics	1
Ever breastfed	Other	1
Ever unemployed (from Wave 2 - Wave 4)	SES - Employment & Labour Market Characteristics	1
Experience of violence	Adversities	1
Externalising behaviours	Personality	1
Family affluence scale	SES - General	1
Family dysfunction	Family factors	1
Family living arrangement	Family factors	1
Family SES measure (education/occupation/household income)	SES - General	1

Family stress	Family factors	1
Family structure	Family factors	1
Farmer status (live/work on farm)	Family factors	1
Finances (as stressor)	SES - Income/Wealth	1
Financial security affected (due to GFC)	SES - Income/Wealth	1
Foreign born	Demographics	1
Functional disability	Physical Health	1
Gender division of household labour	Relationship	1
General health	Physical Health	1
Gestation period	Other	1
GFC salience	Other	1
Gratitude	Personality	1
Hazardous use of alcohol	Alcohol/Smoking/Drug use	1
Health care use	Other	1
Health enhancing behaviours	Physical Health	1
Health insurance	Other	3
Health problems (up to age 25)	Physical Health	1
Health status scale	Physical Health	1
Health/depression status of child's other parent	Relationship	1
History of partner abuse	Adversities	1
Home owner (Y/N)	SES - Income/Wealth	2
Homeowner (yes/no)	SES - Income/Wealth	1
Hours per day spent caregiving	Family factors	1
Household composition	Family factors	1
Household disrepair	SES - Housing	1
Household equivalised disposable income	SES - Income/Wealth	1
Household income	SES - Income/Wealth	3
Household income (60% of median equalised household income)	SES - Income/Wealth	2
Household income (annual)	SES - Income/Wealth	3
Household income (equivalised)	SES - Income/Wealth	2
Household income (net monthly)	SES - Income/Wealth	1
Household income (per capita)	SES - Income/Wealth	1
Household income (quartile)	SES - Income/Wealth	1
Household income loss	SES - Income/Wealth	1
Household income per person-month	SES - Income/Wealth	1
Household income-to-needs ratio	SES - Income/Wealth	1
Household members	Family factors	1
Household size	Family factors	1
Household type (i.e., number of adults and dependent children)	Family factors	1
Housing Affordability Stress (HAS)	SES - Income/Wealth	1
Housing contract	SES - Housing	1
Housing quality	SES - Housing	1
Housing Tenure	SES - Housing	4
Housing tenure (at 7/5)	SES - Housing	1
Immigrant status	Demographics	1
Immigration status	Demographics	1
Income	SES - Income/Wealth	5
Income (by poverty threshold)	SES - Income/Wealth	1
Income level (quartile)	SES - Income/Wealth	1
Income Poverty	SES - Income/Wealth	2
Income quintile	SES - Income/Wealth	1
Income to needs ratio	SES - Income/Wealth	1
Increased household arguments	Relationship	1
Indigenous status	Demographics	1
Individual racism	Adversities	1
Instrumental support	Other	2

Interpersonal support	Other	1
Interpersonal trust	Other	1
Job control	Mastery/Locus of Control	1
Job demand	Other	1
Job fit	Other	1
Job meaning	Other	1
Job search activity	Other	1
Keyworker	Other	1
Language	Demographics	1
Language spoken at home	Demographics	2
Length of receipt of social welfare benefits	SES - General	1
Length of time on welfare	SES - General	1
Length of unemployment	SES - Employment & Labour Market Characteristics	2
Living alone	Relationship	3
Living in a metropolitan area	Demographics	1
Living in an area that experienced lockdown	COVID-19	1
Living in formal housing	SES - Housing	1
Living with a romantic partner	Relationship	1
Living with partner	Relationship	2
Log of equivalised household income	SES - Income/Wealth	2
Log. of secured debt/income	SES - Income/Wealth	1
Log. of unsecured debt/income	SES - Income/Wealth	1
Loneliness	Mental Health	2
Loneliness (as stressor)	Mental Health	1
Long-term illness	Physical Health	1
Lost job	SES - Employment & Labour Market Characteristics	1
Low household income	SES - Income/Wealth	1
Low labour income	SES - Income/Wealth	1
Low occupational status	SES - Employment & Labour Market Characteristics	1
Low personal income	SES - Income/Wealth	1
Marital status	Relationship	38
Marital status (caregiver)	Relationship	1
Marital stress	Relationship	1
Mastery	Mastery/Locus of Control	3
Material deprivation	SES - Hardship	1
Material standard of living score	SES - General	1
Maternal age (at birth)	Other	1
Mature age student (yes/no)	Other	1
Median income	SES - Income/Wealth	1
Median wealth	SES - Income/Wealth	1
Member of occupational pension plan	Other	1
Mother reported total annual per capita family income / number of household members	SES - Income/Wealth	1
Mother smoked during pregnancy	Alcohol/Smoking/Drug use	1
Mother support	Other	1
Mother worked in first 5 years	Other	1
Motherhood	Other	1
Mothers first birth or not	Other	1
Moved home (in past year)	SES - Housing	1
Negative affectivity	Mental Health	1
Negative life events	Adversities	1
Neighbourhood disorder	Neighbourhood factors	1
Neighbourhood hazards	Neighbourhood factors	1
Neighbourhood problems	Neighbourhood factors	1
Neighbourhood quality	Neighbourhood factors	1
No. of adults in household	Family factors	1
No. of Dependent Children	Family factors	11

No. of dependent children - 6 or younger	Family factors	1
No. of dependent children - aged 7 to 17	Family factors	1
No. of school grades repeated	SES - Education	1
Number of work hours	SES - Employment & Labour Market Characteristics	2
Obstetric factors (various)	Other	2
Occupational class	SES - Employment & Labour Market Characteristics	7
Other non-housing wealth	SES - Income/Wealth	1
Overall health (past 4 weeks)	Physical Health	1
Overall relationships	Relationship	1
Owner occupancy of home	SES - Housing	1
Owns home	SES - Housing	1
Parent/caregiver hospitalised with mental illness	Family factors	1
Parent/caregiver incarcerated	Family factors	1
Parent/caregiver with a substance use problem	Family factors	1
Parental citizenship	Demographics	1
Parental education (at 0)	SES - General	1
Parental education (highest level achieved)	SES - General	1
Parental income	SES - Income/Wealth	1
Parental social class (at 0)	SES - General	1
Parental status	Relationship	2
Parenting stress scale	Relationship	1
Parents' combined annual income (before tax)	SES - Income/Wealth	1
Parents' education level	Demographics	1
Parents marital status (at 0)	Relationship	1
Parity	Other	1
Partner depression	Relationship	1
Partner status	Relationship	3
Partner support	Relationship	2
Partner's educational and employment status	SES - General	1
Peer problems	Adversities	1
Perceived gender discrimination	Adversities	1
Perceived social support	Other	1
Percentage of African American residents	Demographics	1
Perception of susceptibility (COVID-19)	COVID-19	1
Perceptions of stress	Mental Health	1
Personal control (Locus of control & self-esteem)	Mastery/Locus of Control	1
Personal outlook	Mastery/Locus of Control	1
Physical activity	Physical Health	2
Physical health	Physical Health	4
Physical need (w. basic functions/activities)	Physical Health	1
Positive COVID experiences	COVID-19	1
Prayer	Other	1
Pre-existing depressive symptoms	Mental Health	2
Pre-existing major depression	Mental Health	2
Pre-existing mental condition	Mental Health	2
Pre-existing neurological disease	Mental Health	1
Pre-existing physical illness	Mental Health	1
Pre-existing psychological distress	Mental Health	1
Pre-existing symptoms of anxiety/depression	Mental Health	2
Pre-lockdown depression score	Mental Health	1
Pre-pandemic household income	SES - Income/Wealth	1
Presence of children in household	Family factors	8
Presence of chronic health conditions	Physical Health	15
Previous clinical diagnosis of depression	Mental Health	1
Previous mental illness	Mental Health	1
Primary care physician visits	Physical Health	1

Prior depressive symptoms	Mental Health	1
Prior economic hardship	SES - Hardship	1
Prior food insecurity	SES - Hardship	1
Prior mental health (at age 19)	Mental Health	1
Problems with daily living activities	Physical Health	1
Race discrimination	Adversities	2
Racial minority	Demographics	1
Read to (at 7/5)	Other	1
Received home delivered meals	Other	1
Recent changes in household income	SES - Income/Wealth	1
Recent injury	Physical Health	1
Recent life events	Adversities	1
Recent/current financial hardship	SES - Hardship	1
Region	Demographics	1
Region (rural/metro)	Demographics	4
Region (Wales, Scotland, Northern Ireland, English)	Demographics	1
Region of birth	Demographics	1
Region of origin	Demographics	1
Region of residence	Demographics	3
Regular employment	SES - Employment & Labour Market Characteristics	1
Regular job in household	SES - Employment & Labour Market Characteristics	1
Relationship quality	Relationship	1
Relationship satisfaction	Relationship	1
Relationship status	Relationship	4
Religious involvement	Other	1
Religious service attendance	Other	1
Remoteness	Demographics	2
Retirement status	Demographics	1
Return to Parental Home	SES - Housing	1
Role/emotional functioning	Mental Health	1
Self-Efficacy	Mastery/Locus of Control	1
Self-esteem	Personality	1
Self-feedback parameter	Other	1
Self-rated health	Physical Health	10
Self-rated mental health	Mental Health	1
Sense of coherence	Personality	1
Sense of community	Neighbourhood factors	2
Sense of control	Mastery/Locus of Control	1
Sense of place	Other	1
Separated from child for more than a month (< age 5)	Other	1
SES	SES - General	1
Sex	Demographics	57
Sex (child)	Demographics	1
Sex discrimination	Adversities	2
Sexual abuse (during childhood)	Adversities	1
Sexual minority	Demographics	1
Sexual satisfaction	Relationship	1
SF-12 physical function	Physical Health	3
SF-12 physical health	Physical Health	2
Sleeping difficulties	Physical Health	1
Smoking status	Alcohol/Smoking/Drug use	5
Social capital	Neighbourhood factors	1
Social class	SES - General	1
Social isolation	Other	2
Social networks (Berkman Syme Index)	Other	1
Social relationship satisfaction	Other	1

Social support (family)	Family factors	1
Social support (friend)	Other	1
Social support (friends and family)	Family factors	3
Social support / Welfare Receipt	Other	4
Social support behaviours of partner	Relationship	1
Social undermining behaviours of partner	Relationship	1
Socioeconomic status (combination of parents education and occupation)	SES - General	1
Spiritual practices	Other	1
State (Iowa/Georgia)	Demographics	1
Stigma	Adversities	1
Strain from limited peer contact	Adversities	1
Stressful life circumstances	Adversities	2
Subsequent unemployment (in waves post baseline)	SES - Employment & Labour Market Characteristics	1
Supervisor support	Other	1
Support and assistance received in previous month for food and shelter	SES - Hardship	1
Survey wave	Study Methodology/Factors	5
Survey year	Study Methodology/Factors	1
Taking care of an elderly person	Other	1
Tested positive for COVID	COVID-19	1
Time (mean-centred)	Study Methodology/Factors	1
Time in Australia	Demographics	1
Time interval since previous assessment	Study Methodology/Factors	1
Time since first wave of data collection	Study Methodology/Factors	2
Time since lockdown began	COVID-19	2
Total household income (at 0)	SES - Income/Wealth	1
Type of housing arrangement	SES - Housing	1
Type of housing tenancy	SES - Housing	1
Type of work	SES - Employment & Labour Market Characteristics	1
Unemployment	SES - Employment & Labour Market Characteristics	2
Unemployment negativity (how upsetting being unemployed is)	SES - Employment & Labour Market Characteristics	1
Urban location	Neighbourhood factors	1
Value of home	SES - Income/Wealth	1
View of student loan	Other	1
Volunteering	Other	1
Wealth Index	SES - Income/Wealth	1
Weight/shape dissatisfaction	Other	1
Work from home	Other	1
Work/Study	Other	1
Year	Study Methodology/Factors	1
Years of caregiving	Other	1
Zifune intervention	Other	1

Appendix A.14

Multivariate outcomes by the proportion of males in sample.

Sample Characteristics	No		Yes	
	n	%	n	%
% Males in Sample				
0	2	9.1%	20	90.9%
0 - 10				
10 - 20	1	25.0%	3	75.0%
20 - 30	3	33.3%	6	66.7%
30 - 40	1	7.7%	12	92.3%
40 - 50	5	10.4%	43	89.6%
50 - 60	3	23.1%	10	76.9%
60 - 70			2	100.0%
70 - 80			1	100.0%
80 - 90			1	100.0%
90 - 100			3	100.0%

Appendix A.15

Outcomes by surveys/datasets used within included studies.

** Note, the Born in Bradford survey* (Dickerson et al., 2022) *and the Panel study of Belgian Households (PSBH)* (Lorant et al., 2007) *did not contain any multivariate assessment of the relationship between financial hardship experience and mental health.*

Survey / Dataset	No		Yes		Total	
	n	%	n	%	n	%
* Not Stated / Not Named	4	17.4%	19	82.6%	**23**	**100.0%**
1958 National Child Development Study; 1970 British Cohort Study (BCS70)			1	100.0%	**1**	**100.0%**
2000 Psychiatric Morbidity Survey	2	66.7%	1	33.3%	**3**	**100.0%**
Alameda County Study			1	100.0%	**1**	**100.0%**
Annual Living Conditions Survey (ULF)			1	100.0%	**1**	**100.0%**
Arizona Pathways to Life Success for University Students (APLUS)			1	100.0%	**1**	**100.0%**
Australian Longitudinal Study on Women's Health (ALSWH)			1	100.0%	**1**	**100.0%**
Australian National COVID-19 Mental Health, Behaviour and Risk Communication Survey			2	100.0%	**2**	**100.0%**
Australian Rural Mental Health Study (ARMHS)			3	100.0%	**3**	**100.0%**
Born in Bradford Study						
British Household Panel Study (BHPS); UK Household Longitudinal Study (UKHLS)			1	100.0%	**1**	**100.0%**
Building a New Life in Australia Study (BNLA)			2	100.0%	**2**	**100.0%**
California Families Project			1	100.0%	**1**	**100.0%**
Canadian Quality of Work and Economic Life Study (C-QWELS)			1	100.0%	**1**	**100.0%**
Canadian Work, Stress, and Health Study (CAN-WSH)			1	100.0%	**1**	**100.0%**
Child Development Study (CDS)			1	100.0%	**1**	**100.0%**
Chinese Longitudinal Healthy Longevity Survey (CLHLS)			1	100.0%	**1**	**100.0%**
Corona Immunitas Digital Follow-Up (CI-DFU)			3	100.0%	**3**	**100.0%**
COVID-19 Social Study			2	100.0%	**2**	**100.0%**
COVID-19 survey (UK)			2	100.0%	**2**	**100.0%**
Early Childhood Longitudinal Study-Birth Cohort (ECLS-B)			1	100.0%	**1**	**100.0%**
European Longitudinal Cohort Study of Pregnancy and Childhood - Czech (ELSPAC-CZ)			1	100.0%	**1**	**100.0%**
Family and Community Health Study (FACHS)			1	100.0%	**1**	**100.0%**
Fragile Families and Child Wellbeing Study (FFCWS)			3	100.0%	**3**	**100.0%**
German Socio-Economic Panel (SOEP) study			1	100.0%	**1**	**100.0%**
GoWell			1	100.0%	**1**	**100.0%**
Growing Up in Ireland			1	100.0%	**1**	**100.0%**
Health and Retirement Study (HRS)			1	100.0%	**1**	**100.0%**
Household Income and Labour Dynamics of Australia Survey (HILDA)			4	100.0%	**4**	**100.0%**
Iowa Youth and Families Project (IYFP)			1	100.0%	**1**	**100.0%**
Korea Welfare Panel Study (KOWEPS)			4	100.0%	**4**	**100.0%**
Life Course Perspective and Dropout from Higher Education (LAST)			1	100.0%	**1**	**100.0%**
Life Patterns			1	100.0%	**1**	**100.0%**
Longitudinal Midlife in the United States (MIDUS) study			2	100.0%	**2**	**100.0%**

Miami Disability Study			2	100.0%	**2**	**100.0%**
National Income Dynamics Study–Coronavirus Rapid Mobile Survey (NIDS-CRAM)			1	100.0%	**1**	**100.0%**
National Longitudinal Study on Alcohol and Related Conditions (NESARC)			3	100.0%	**3**	**100.0%**
National Population Health Survey (NPHS)			1	100.0%	**1**	**100.0%**
Netherlands Study of Depression and Anxiety (NESDA)	1	100.0%			**1**	**100.0%**
Panel study of Belgian Households (PSBH)						
Personality and Total Health (PATH) Through Life	2	50.0%	2	50.0%	**4**	**100.0%**
PIONEER-COVID-19 study			1	100.0%	**1**	**100.0%**
Resources for Enhancing Alzheimer's Caregiver Health (REACH)			1	100.0%	**1**	**100.0%**
Rural Families Speak (NC-223)			1	100.0%	**1**	**100.0%**
Southampton Women's Survey (SWS)	1	100.0%			**1**	**100.0%**
Stockholm Public Health Cohort (SPHC)			1	100.0%	**1**	**100.0%**
Survey of Family, Income and Employment (SoFIE)			2	100.0%	**2**	**100.0%**
Swedish Level of Living Survey (LNU); Swedish Panel Study of Living Conditions among the Oldest Old (SWEOLD)			1	100.0%	**1**	**100.0%**
Swiss Household Panel (SHP)			1	100.0%	**1**	**100.0%**
Taiwan Database of Children and Youth in Poverty (TDCYP)			1	100.0%	**1**	**100.0%**
Taiwan Longitudinal Study on Aging (TLSA)			2	100.0%	**2**	**100.0%**
Trajectoires Epide´Miologiques en POpulation (TEMPO) - Additional COVID-19 survey	1	100.0%			**1**	**100.0%**
Trends and Implications of Poverty and Social Disadvantages in Hong Kong	1	50.0%	1	50.0%	**2**	**100.0%**
UK Household Longitudinal Study - COVID-19 Survey (UKHLS)			1	100.0%	**1**	**100.0%**
Welfare, Children, and Families Project (WCF)			2	100.0%	**2**	**100.0%**
Well-Being Survey	1	33.3%	2	66.7%	**3**	**100.0%**
Whitehall II	2	66.7%	1	33.3%	**3**	**100.0%**
WHO-SAGE Survey (Ghana Component)			1	100.0%	**1**	**100.0%**
Women's Employment Study (WES)			2	100.0%	**2**	**100.0%**
Yale Health and Ageing Project (YHAP)			1	100.0%	**1**	**100.0%**
Young Lives Study			2	100.0%	**2**	**100.0%**

Appendix A.16

Multivariate outcomes by study characteristics.

Study Characteristic	No		Yes		Total	
	n	%	n	%	n	%
Publication Year						
1987			1	100.0%	**1**	**100.0%**
1989						
1994			1	100.0%	**1**	**100.0%**
1996			1	100.0%	**1**	**100.0%**
1997			1	100.0%	**1**	**100.0%**
1999			1	100.0%	**1**	**100.0%**
2000						
2002			2	100.0%	**2**	**100.0%**
2003			4	100.0%	**4**	**100.0%**
2004			1	100.0%	**1**	**100.0%**
2005			1	100.0%	**1**	**100.0%**
2006	2	66.7%	1	33.3%	**3**	**100.0%**
2007			1	100.0%	**1**	**100.0%**
2008	1	100.0%			**1**	**100.0%**
2009	1	20.0%	4	80.0%	**5**	**100.0%**
2010			2	100.0%	**2**	**100.0%**
2011	1	20.0%	4	80.0%	**5**	**100.0%**
2012			1	100.0%	**1**	**100.0%**
2014			8	100.0%	**8**	**100.0%**
2015	1	20.0%	4	80.0%	**5**	**100.0%**
2016			6	100.0%	**6**	**100.0%**
2017	3	50.0%	3	50.0%	**6**	**100.0%**
2018			10	100.0%	**10**	**100.0%**
2019			5	100.0%	**5**	**100.0%**
2020	3	33.3%	6	66.7%	**9**	**100.0%**
2021	1	5.9%	16	94.1%	**17**	**100.0%**
2022	2	15.4%	11	84.6%	**13**	**100.0%**
2023			6	100.0%	**6**	**100.0%**
Survey Setting						
Local	3	15.0%	17	85.0%	**20**	**100.0%**
Regional	3	13.6%	19	86.4%	**22**	**100.0%**
Regional; Local	1	20.0%	4	80.0%	**5**	**100.0%**
National	8	11.9%	59	88.1%	**67**	**100.0%**
International			2	100.0%	**2**	**100.0%**
Survey Waves						
2	10	23.8%	32	76.2%	**42**	**100.0%**
3	1	3.0%	32	97.0%	**33**	**100.0%**
4	3	15.8%	16	84.2%	**19**	**100.0%**
5			7	100.0%	**7**	**100.0%**
6			4	100.0%	**4**	**100.0%**
7			2	100.0%	**2**	**100.0%**
8			1	100.0%	**1**	**100.0%**
9	1	50.0%	1	50.0%	**2**	**100.0%**
10			2	100.0%	**2**	**100.0%**
12			1	100.0%	**1**	**100.0%**
19			2	100.0%	**2**	**100.0%**

20			1	100.0%	**1**	**100.0%**
Survey Wave Interval (Months)						
0.25	1	33.3%	2	66.7%	**3**	**100.0%**
0.5			2	100.0%	**2**	**100.0%**
1			2	100.0%	**2**	**100.0%**
2						
3	3	50.0%	3	50.0%	**6**	**100.0%**
4	1	12.5%	7	87.5%	**8**	**100.0%**
5			2	100.0%	**2**	**100.0%**
6			12	100.0%	**12**	**100.0%**
8			1	100.0%	**1**	**100.0%**
9			6	100.0%	**6**	**100.0%**
12	1	3.6%	27	96.4%	**28**	**100.0%**
18	3	60.0%	2	40.0%	**5**	**100.0%**
24	3	15.8%	16	84.2%	**19**	**100.0%**
36	3	25.0%	9	75.0%	**12**	**100.0%**
48			5	100.0%	**5**	**100.0%**
60			1	100.0%	**1**	**100.0%**
72			1	100.0%	**1**	**100.0%**
96			1	100.0%	**1**	**100.0%**
108			2	100.0%	**2**	**100.0%**
Study Span (Years)						
0-1	2	9.5%	19	90.5%	**21**	**100.0%**
1-2	6	30.0%	14	70.0%	**20**	**100.0%**
2-3	2	16.7%	10	83.3%	**12**	**100.0%**
3-4	1	8.3%	11	91.7%	**12**	**100.0%**
4-5	3	27.3%	8	72.7%	**11**	**100.0%**
5-6	1	20.0%	4	80.0%	**5**	**100.0%**
6-7			4	100.0%	**4**	**100.0%**
7-8			5	100.0%	**5**	**100.0%**
8-9			4	100.0%	**4**	**100.0%**
9-10			2	100.0%	**2**	**100.0%**
10-11			1	100.0%	**1**	**100.0%**
11-12			3	100.0%	**3**	**100.0%**
13-14			3	100.0%	**3**	**100.0%**
15-16			1	100.0%	**1**	**100.0%**
16-17			1	100.0%	**1**	**100.0%**
17-18			2	100.0%	**2**	**100.0%**
18-19			1	100.0%	**1**	**100.0%**
23-24			1	100.0%	**1**	**100.0%**

Appendix A.17

Multivariate outcomes by number of items and domains assessed within financial hardship measures.

** Note, this table only details the results from assessments that were produced using multi-item or individual item measures of financial hardship. The results of assessments that used a measures of financial hardship implemented with a 'general' financial question are not detailed in the table below.*

Outcome	No		Yes		Total	
	n	%	n	%	n	%
FH - No. of Items						
1			12	100.0%	**12**	**100.0%**
2			11	100.0%	**11**	**100.0%**
3	2	15.4%	11	84.6%	**13**	**100.0%**
4	3	30.0%	7	70.0%	**10**	**100.0%**
5			2	100.0%	**2**	**100.0%**
6			4	100.0%	**4**	**100.0%**
7			9	100.0%	**9**	**100.0%**
8	5	50.0%	5	50.0%	**10**	**100.0%**
9	1	100.0%			**1**	**100.0%**
10			1	100.0%	**1**	**100.0%**
12			1	100.0%	**1**	**100.0%**
13			2	100.0%	**2**	**100.0%**
18			2	100.0%	**2**	**100.0%**
21	1	50.0%	1	50.0%	**2**	**100.0%**
32			1	100.0%	**1**	**100.0%**
FH - No. of Domains Assessed						
1	1	4.3%	22	95.7%	**23**	**100.0%**
2			9	100.0%	**9**	**100.0%**
3	2	28.6%	5	71.4%	**7**	**100.0%**
4	3	33.3%	6	66.7%	**9**	**100.0%**
5			2	100.0%	**2**	**100.0%**
6			3	100.0%	**3**	**100.0%**
7	1	12.5%	7	87.5%	**8**	**100.0%**
8	5	50.0%	5	50.0%	**10**	**100.0%**
10			1	100.0%	**1**	**100.0%**

Appendix A.18

Risk of Bias Assessment – Joanna Briggs Institute Checklist for Cohort Studies

Author(s)	Pub. Yr.	Reviewer	Were the two groups similar and recruited from the same population?	Were the exposures measured similarly to assign people to both exposed and unexposed groups?	Were confounding factors identified?	Were strategies to deal with confounding factors stated?	Were the groups/participants free of the outcome at the start of the study (or at the moment of exposure)?	Were the outcomes measured in a valid and reliable way?	Was the follow up time reported and sufficient to be long enough for outcomes to occur?	Was follow up Was follow up complete, and if not, were the reasons to loss to follow up described and explored?	Were strategies to address incomplete follow up utilized?	Was appropriate statistical analysis used?	Were the criteria for inclusion in the sample clearly defined?	Were the study subjects and the setting described in detail?
Krause	1987	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Krause	1987	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jones	1989	CC	Yes	Yes	Unclear	No	Unclear	Yes	No	Yes	No	No	No	No
Jones	1989	JT	Yes	Yes	No	No	Unclear	Yes	No	Yes	No	No	No	No
Mendes et al	1994	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mendes et al	1994	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Unclear	No	Yes	Yes	Yes
Vinokur et al	1996	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vinokur et al	1996	SO	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Roberts et al	1997	SO	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Roberts et al	1997	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Conger et al	1999	JT	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes
Conger et al	1999	SO	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes
Roberts et al	2000	SO	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Roberts et al	2000	JT	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Lai et al	2002	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	No
Lai et al	2002	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Unclear	Yes	Yes
Price et al	2002	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Price et al	2002	SO	Yes	Yes	No	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Waters et al	2003	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Waters et al	2003	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	No	No
Siefert et al	2004	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Unclear	Yes	Yes	Yes
Siefert et al	2004	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Heflin et al	2005	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Heflin et al	2005	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Unclear	Yes	Yes	Yes
Skapinakis et al	2006	SO	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes
Skapinakis et al	2006	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ahnquist et al	2007	JT	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes
Ahnquist et al	2007	SO	Yes	Yes	Yes	Yes	No	Unclear	Yes	No	Unclear	Yes	Yes	Yes

Lorant et al	2007	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	Yes	Yes	Yes	Yes
Lorant et al	2007	CC	Yes	Yes	Yes	No	Unclear	Yes	Yes	No	Yes	Yes	Yes	Yes
Dunn et al	2008	JT	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Dunn et al	2008	SO	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	Yes
Butterworth et al	2009	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Butterworth et al	2009	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chiao et al	2009	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chiao et al	2009	SO	Yes	Yes	Unclear	Unclear	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Heflin et al	2009	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Heflin et al	2009	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Huddleston-Casas et al	2009	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Huddleston-Casas et al	2009	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Krause	2009	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Krause	2009	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
Wang et al	2010	JT	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Unclear	Yes	Yes	Yes
Wang et al	2010	SO	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Unclear	Yes	Yes	Yes
Xiaowan et al	2010	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Xiaowan et al	2010	CC	Yes	Yes	Yes	Yes	Unclear	No	Unclear	Yes	Yes	Yes	Yes	Yes
Burdette et al	2011	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Unclear	Yes	Yes	Yes
Burdette et al	2011	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Cole et al	2011	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Unclear	Yes	Yes	Yes	Yes	Yes
Cole et al	2011	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Howden-Chapman et al	2011	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Howden-Chapman et al	2011	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Unclear	Yes	Yes	Yes
Sargent-Cox et al	2011	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Sargent-Cox et al	2011	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
Manuel et al	2012	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manuel et al	2012	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chen et al	2014	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chen et al	2014	SO	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Frank et al	2014	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Frank et al	2014	SO	Yes	Yes	No	No	No	Yes	No	Yes	No	Yes	Yes	Yes
Maclean et al	2014	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maclean et al	2014	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mckenzie et al	2014	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mckenzie et al	2014	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Dijkstra-Kersten et al	2015	TS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Dijkstra-Kersten et al	2015	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Drentea et al	2015	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drentea et al	2015	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kiely et al	2015	TS	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Unclear	Unclear	Yes	Yes	Yes
Kiely et al	2015	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Unclear	Unclear	Yes	Yes	Yes
Maclean et al	2015	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maclean et al	2015	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crowe et al	2016	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crowe et al	2016	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crowe et al	2016	TS	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crowe et al	2016	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Curl et al	2016	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
Curl et al	2016	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
Holden et al	2016	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holden et al	2016	SO	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Landstedt et al	2016	JT	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes
Landstedt et al	2016	CC	Yes	Yes	Yes	Yes	Unclear	No	Yes	No	No	Yes	Yes	Yes
Nam	2016	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Nam	2016	TS	Yes	Yes	Yes	Yes	Not Applicable	Yes	Yes	No	No	Yes	Yes	Yes
Barthel et al	2017	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Barthel et al	2017	TS	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
French	2017	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
French	2017	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
Richardson et al	2017	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Richardson et al	2017	TS	Yes	Yes	Yes	Yes	Not Applicable	Yes	Yes	No	No	Yes	Yes	Yes
Austin et al	2018	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Austin et al	2018	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Butterworth et al	2018	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Butterworth et al	2018	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Darin-Mattsson et al	2018	TS	Yes	Yes	Yes	Yes	No	No	Yes	No	No	Yes	Yes	Yes
Darin-Mattsson et al	2018	JT	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes
Kim et al	2018	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Kim et al	2018	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
Koltai et al	2018	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Koltai et al	2018	TS	Yes	Yes	Yes	Yes	Not Applicable	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Mccarthy et al	2018	CC	Yes	Yes	Yes	Yes	Unclear	Unclear	Unclear	No	Yes	Yes	Yes	Yes
Mccarthy et al	2018	JT	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	No	Yes	Yes	Yes	Yes
Russell et al	2018	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Unclear	Unclear	Yes	Yes	Yes
Russell et al	2018	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Unclear	Unclear	Yes	Yes	Yes
Winzer et al	2018	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	No	Yes	Yes	Yes
Winzer et al	2018	TS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Wu et al	2018	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Wu et al	2018	TS	Yes	Yes	No	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Cooper et al	2019	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cooper et al	2019	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forbes et al	2019	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forbes et al	2019	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	Yes	Yes	Yes	Yes
Handley et al	2019	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Handley et al	2019	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Whitsett et al	2019	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Whitsett et al	2019	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Chung et al	2020	PB	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes	No	Yes	No
Chung et al	2020	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Hashmi et al	2020	TS	Yes	Yes	Yes	Yes	Not Applicable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hashmi et al	2020	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Klug et al	2020	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Klug et al	2020	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lyu et al	2020	TS	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes
Lyu et al	2020	JT	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes
Stepanikova et al	2020	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Stepanikova et al	2020	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Steptoe et al	2020	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Steptoe et al	2020	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No
Torlinska et al	2020	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Torlinska et al	2020	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Amegbor et al	2021	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	Yes	Yes	Yes	Yes
Amegbor et al	2021	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	Yes	Yes	Yes	Yes
Batterham et al	2021	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Batterham et al	2021	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Bialowolski et al	2021	PB	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bialowolski et al	2021	JT	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Bierman et al	2021	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bierman et al	2021	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cao et al	2021	PB	Yes	Yes	Yes	Yes	No	Unclear	Yes	Yes	Yes	Yes	Not Applicable	Yes
Cao et al	2021	JT	Yes	Yes	Yes	Yes	No	Unclear	Yes	Yes	Yes	Yes	Yes	Yes
Kang et al	2021	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Kang et al	2021	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Lee et al	2021	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Lee et al	2021	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Unclear	Yes	Yes
Lee et al	2021	PB	Yes	Yes	Yes	Yes	No	Yes	Not Applicable	Unclear	Unclear	Yes	Yes	No
Lee et al	2021	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Pierce et al	2021	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Pierce et al	2021	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Porter et al	2021	JT	Yes	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	Yes
Porter et al	2021	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Preetz et al	2021	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
Preetz et al	2021	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
Wright et al	2021	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Wright et al	2021	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Cho	2022	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cho	2022	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	Yes
Dickerson et al	2022	PB	Yes	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	Yes
Dickerson et al	2022	JT	Yes	Yes	Yes	No	No	Yes	Yes	No	No	No	Yes	Yes
Finnbogadã³Ttir et al	2022	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Unclear	Yes	Yes
Finnbogadã³Ttir et al	2022	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Unclear	Yes	Yes
Haag et al	2022	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Unclear	Unclear	Yes	Yes	Yes
Haag et al	2022	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Unclear	Yes	Yes	Yes	Yes
Hecker et al	2022	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hecker et al	2022	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marshall et al	2022	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Unclear	Unclear	Yes	Yes	Yes
Marshall et al	2022	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Unclear	Unclear	Yes	No	Yes
Mohan	2022	TS	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Mohan	2022	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Moreno-Agostino et al	2022	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Moreno-Agostino et al	2022	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Porter et al	2022	JT	Yes	Yes	No	No	No	Yes	Not Applicable	Not Applicable	No	No	Unclear	No
Porter et al	2022	PB	Yes	Yes	No	No	No	Yes	Not Applicable	Not Applicable	No	No	Unclear	No

Shepherd	2022	JT	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	Yes	Yes	Yes	Yes
Shepherd	2022	CC	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	Yes	Yes	Yes	Yes
Sommet et al	2022	CC	Yes	Yes	Yes	Yes	Unclear	No	Yes	No	Yes	Yes	Yes	Yes
Sommet et al	2022	JT	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes
Stein et al	2022	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stein et al	2022	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zhang et al	2022	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Zhang et al	2022	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Bentley et al	2023	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Bentley et al	2023	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Choi et al	2023	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Choi et al	2023	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes
Moulton et al	2023	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Moulton et al	2023	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes			
Tancredi et al	2023	JT	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tancredi et al	2023	PB	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix B – Supplementary Material for Chapter 3

Appendix B.1

SEIFA Index of Relative Socio-Economic Advantage and Disadvantage

1. The percentage of people aged 15 years and over whose highest level of education is Year 11 or lower. Includes Certificate I and II
2. The percentage of people living in households with stated annual household equivalised income between \$1 and \$25,999 (approx. 1st and 2nd deciles)
3. The percentage of employed people classified as 'labourers'
4. The percentage of people aged under 70 who need assistance with core activities due to a long–term health condition, disability, or old age
5. The percentage of families with children under 15 years of age who live with jobless parents
6. The percentage of employed people classified as Machinery Operators and Drivers
7. The percentage of occupied private dwellings paying rent less than \$250 per week (excluding \$0 per week)
8. The percentage of people aged 15 and over who are separated or divorced
9. The percentage of one parent families with dependent offspring only
10. The percentage of people (in the labour force) unemployed
11. The percentage of employed people classified as Low Skill Community and Personal Service Workers
12. The percentage of people aged 15 years and over whose highest level of educational attainment is a certificate III or IV qualification
13. The percentage of occupied private dwellings requiring one or more extra bedrooms (based on Canadian National Occupancy Standard)
14. The percentage of people aged 15 years and over who have no educational attainment
15. The percentage of employed people classified as Low Skill Sales
16. The percentage of people aged 15 years and over at university or other tertiary institution
17. The percentage of occupied private dwellings with four or more bedrooms
18. The percentage of people aged 15 years and over whose highest level of education attainment is a diploma qualification
19. The percentage of occupied private dwellings paying rent greater than \$470 per week
20. The percentage of employed people classified as Managers
21. The percentage of occupied private dwellings paying mortgage greater than \$2,800 per month
22. The percentage of employed people classified as Professionals
23. The percentage of people living in households with stated annual household equivalised income greater than \$91,000 (approx. 9th and 10th deciles)

Appendix B.2

10-item SF-36 Physical Functioning subscale of the SF-36 Health Survey

Specifically, respondents are asked, ‘During the past 4 weeks, did your health limit you in these activities? If so, how much?’

1. Vigorous activities, such as running, lifting heavy objects, or participating in strenuous sports.
2. Moderate activities, such as moving a table, pushing a vacuum cleaner, bowling, or playing golf.
3. Lifting or carrying groceries
4. Climbing several flights of stairs
5. Climbing one flight of stairs
6. Bending kneeling or stooping
7. Walking more than one kilometre
8. Walking half a kilometre
9. Walking 100 metres
10. Bathing or dressing yourself

Each item is answered across a three-level response continuum: (1) “Yes, limited a lot”; (2) “Yes, limited a little”; (3) “No, not limited at all”.

Appendix B.3

5-item Mental Health (MHI-5) subscale of the SF-36 Health Survey

Specifically, respondents are asked, *'How much of the time during the past 4 weeks'*:

1.	Have you been a nervous person.
2.	Have you felt so down in the dumps nothing could cheer you up.
3.	Have you felt calm and peaceful.
4.	Have you felt downhearted and blue.
5.	Have you been a happy person.

Respondents answer each item over a 6-point Likert scale, by selecting either (1) "All of the time"; (2) "Most of the time"; (3) "A good bit of the time"; (4) "Some of the time"; (5) "A little of the time"; (6) "None of the time".

Appendix B.4

Tables detailing estimated prevalence of financial hardship, cashflow problems, and deprivation, along with estimates of the same outcomes after removing data from respondents' first year of HILDA Survey participation.

	Financial Hardship					Financial Hardship - minus first year of HILDA participation				
Year	**n**	**n (weighted)**	**FH n (weighted)**	**FH % (weighted)**	**FH 95% CI**	**n**	**n (weighted)**	**FH n (weighted)**	**FH % (weighted)**	**FH 95% CI**
2001	13,058	14,923,779	4,374,130	29.31	28.43 - 30.19	0	0	0	0	0
2002	12,130	15,133,844	3,784,761	25.01	24.03 - 25.99	10,831	12,672,170	3,083,167	24.33	23.4 - 25.27
2003	11,747	15,347,574	3,792,231	24.71	23.67 - 25.75	10,922	13,936,923	3,341,563	23.98	22.96 - 24.99
2004	11,397	15,552,868	3,506,283	22.54	21.55 - 23.54	10,700	14,340,361	3,204,209	22.34	21.33 - 23.36
2005	11,465	15,786,018	3,525,490	22.33	21.26 - 23.41	10,717	14,525,039	3,132,082	21.56	20.52 - 22.6
2006	11,688	16,057,442	3,293,486	20.51	19.47 - 21.56	10,870	14,796,219	2,923,052	19.76	18.73 - 20.78
2007	11,381	16,379,640	3,460,929	21.13	20.03 - 22.23	10,728	15,142,055	3,132,179	20.69	19.6 - 21.77
2008	11,193	16,750,326	3,089,749	18.45	17.46 - 19.43	10,555	15,613,389	2,829,674	18.12	17.13 - 19.11
2009	11,563	17,105,835	3,485,673	20.38	19.36 - 21.39	10,803	15,753,545	3,117,819	19.79	18.76 - 20.82
2010	12,052	17,371,743	0	0	0 - 0	11,280	16,180,911	0	0	0 - 0
2011	15,366	17,641,853	4,203,979	23.83	22.82 - 24.84	11,270	11,692,579	2,542,342	21.74	20.69 - 22.8
2012	15,389	17,955,273	3,850,325	21.44	20.55 - 22.33	14,301	16,115,937	3,329,820	20.66	19.78 - 21.54
2013	15,360	18,257,488	3,848,118	21.08	20.13 - 22.02	14,430	16,701,239	3,386,170	20.27	19.35 - 21.2
2014	15,595	18,529,494	3,947,221	21.3	20.41 - 22.2	14,703	17,093,744	3,503,180	20.49	19.62 - 21.37
2015	15,513	18,803,944	3,868,871	20.57	19.65 - 21.49	14,674	17,472,714	3,485,682	19.95	19.04 - 20.86
2016	16,253	19,120,187	3,804,860	19.9	19 - 20.8	15,392	17,815,400	3,508,046	19.69	18.77 - 20.62
2017	16,140	19,451,566	3,492,086	17.95	17.12 - 18.78	15,438	18,431,983	3,253,569	17.65	16.82 - 18.49
2018	15,887	19,781,106	3,918,292	19.81	18.87 - 20.74	15,188	18,560,177	3,591,732	19.35	18.42 - 20.28
2019	16,082	20,108,254	3,947,798	19.63	18.77 - 20.49	15,333	19,011,660	3,607,507	18.98	18.11 - 19.84
2020	15,676	20,298,824	3,966,468	19.54	18.62 - 20.46	15,044	19,176,063	3,647,806	19.02	18.14 - 19.9
2021	15,299	20,373,462	3,698,731	18.15	17.3 - 19.01	14,684	19,336,293	3,438,179	17.78	16.91 - 18.65
2022	14,814	20,791,738	3,821,754	18.38	17.47 - 19.29	14,272	19,811,975	3,545,082	17.89	16.98 - 18.81
2023	14,917	21,437,023	4,632,061	21.61	20.62 - 22.6	14,224	19,343,696	4,160,716	21.51	20.56 - 22.46

Year	Cashflow Problems					Cashflow Problems - minus first year of HILDA participation				
	n	**n (weighted)**	**Cashflow n (weighted)**	**Cashflow % (weighted)**	**Cashflow 95% CI**	**n**	**n (weighted)**	**Cashflow n (weighted)**	**Cashflow % (weighted)**	**Cashflow 95% CI**
2001	13,058	14,923,779	3,934,281	26.36	25.51 - 27.21	0	0	0	0	0
2002	12,130	15,133,844	3,431,134	22.67	21.73 - 23.62	10,831	12,672,170	2,805,842	22.14	21.24 - 23.05
2003	11,747	15,347,574	3,400,539	22.16	21.16 - 23.15	10,922	13,936,923	3,008,056	21.58	20.6 - 22.57
2004	11,397	15,552,868	3,172,648	20.4	19.44 - 21.36	10,700	14,340,361	2,896,275	20.2	19.21 - 21.18
2005	11,465	15,786,018	3,200,682	20.28	19.24 - 21.31	10,717	14,525,039	2,828,757	19.48	18.48 - 20.47
2006	11,688	16,057,442	2,982,259	18.57	17.57 - 19.58	10,870	14,796,219	2,636,665	17.82	16.85 - 18.79
2007	11,381	16,379,640	3,146,111	19.21	18.13 - 20.28	10,728	15,142,055	2,848,130	18.81	17.75 - 19.86
2008	11,193	16,750,326	2,773,917	16.56	15.62 - 17.5	10,555	15,613,389	2,543,220	16.29	15.34 - 17.24
2009	11,563	17,105,835	3,130,047	18.3	17.31 - 19.28	10,803	15,753,545	2,801,855	17.79	16.79 - 18.78
2010	12,052	17,371,743	0	0	0 - 0	11,280	16,180,911	0	0	0 - 0
2011	15,366	17,641,853	3,643,467	20.65	19.71 - 21.59	11,270	11,692,579	2,210,776	18.91	17.92 - 19.89
2012	15,389	17,955,273	3,382,185	18.84	17.99 - 19.68	14,301	16,115,937	2,902,508	18.01	17.18 - 18.84
2013	15,360	18,257,488	3,347,966	18.34	17.43 - 19.24	14,430	16,701,239	2,946,571	17.64	16.75 - 18.53
2014	15,595	18,529,494	3,480,536	18.78	17.93 - 19.64	14,703	17,093,744	3,086,119	18.05	17.22 - 18.89
2015	15,513	18,803,944	3,374,288	17.94	17.06 - 18.83	14,674	17,472,714	3,037,131	17.38	16.5 - 18.26
2016	16,253	19,120,187	3,302,856	17.27	16.4 - 18.14	15,392	17,815,400	3,062,416	17.19	16.29 - 18.09
2017	16,140	19,451,566	3,029,829	15.58	14.78 - 16.37	15,438	18,431,983	2,829,718	15.35	14.55 - 16.15
2018	15,887	19,781,106	3,429,868	17.34	16.43 - 18.25	15,188	18,560,177	3,139,633	16.92	16.01 - 17.82
2019	16,082	20,108,254	3,333,421	16.58	15.76 - 17.4	15,333	19,011,660	3,063,109	16.11	15.28 - 16.94
2020	15,676	20,298,824	3,208,755	15.81	14.96 - 16.65	15,044	19,176,063	2,986,174	15.57	14.73 - 16.41
2021	15,299	20,373,462	3,076,943	15.1	14.31 - 15.89	14,684	19,336,293	2,855,212	14.77	13.96 - 15.57
2022	14,814	20,791,738	3,201,391	15.4	14.53 - 16.26	14,272	19,811,975	2,979,435	15.04	14.16 - 15.92
2023	14,917	21,437,023	3,816,786	17.8	16.89 - 18.72	14,224	19,343,696	3,474,083	17.96	17.06 - 18.86

Year	Deprivation					Deprivation - minus first year of HILDA participation				
	n	n (weighted)	Deprivation n (weighted)	Deprivation % (weighted)	Deprivation 95% CI	n	n (weighted)	Deprivation n (weighted)	Deprivation % (weighted)	Deprivation 95% CI
2001	13,058	14,923,779	1,900,551	12.74	12.09 - 13.38	0	0	0	0	0
2002	12,130	15,133,844	1,523,954	10.07	9.38 - 10.76	10,831	12,672,170	1,204,713	9.51	8.88 - 10.13
2003	11,747	15,347,574	1,595,765	10.4	9.6 - 11.2	10,922	13,936,923	1,375,327	9.87	9.12 - 10.61
2004	11,397	15,552,868	1,357,677	8.73	8.04 - 9.42	10,700	14,340,361	1,243,873	8.67	7.96 - 9.38
2005	11,465	15,786,018	1,361,607	8.63	7.9 - 9.35	10,717	14,525,039	1,235,855	8.51	7.77 - 9.25
2006	11,688	16,057,442	1,214,152	7.56	6.94 - 8.19	10,870	14,796,219	1,108,663	7.49	6.84 - 8.15
2007	11,381	16,379,640	1,365,269	8.34	7.55 - 9.12	10,728	15,142,055	1,218,799	8.05	7.28 - 8.82
2008	11,193	16,750,326	1,283,590	7.66	6.94 - 8.39	10,555	15,613,389	1,186,555	7.6	6.84 - 8.36
2009	11,563	17,105,835	1,567,768	9.17	8.38 - 9.95	10,803	15,753,545	1,372,392	8.71	7.94 - 9.49
2010	12,052	17,371,743	0	0	0 - 0	11,280	16,180,911	0	0	0 - 0
2011	15,366	17,641,853	1,918,828	10.88	10.15 - 11.61	11,270	11,692,579	1,135,458	9.71	8.98 - 10.44
2012	15,389	17,955,273	1,715,900	9.56	8.96 - 10.15	14,301	16,115,937	1,492,344	9.26	8.65 - 9.87
2013	15,360	18,257,488	1,775,216	9.72	9.1 - 10.34	14,430	16,701,239	1,569,668	9.4	8.78 - 10.01
2014	15,595	18,529,494	1,779,258	9.6	8.98 - 10.22	14,703	17,093,744	1,567,386	9.17	8.55 - 9.79
2015	15,513	18,803,944	1,845,464	9.81	9.18 - 10.44	14,674	17,472,714	1,643,801	9.41	8.8 - 10.02
2016	16,253	19,120,187	1,822,205	9.53	8.93 - 10.13	15,392	17,815,400	1,640,049	9.21	8.6 - 9.82
2017	16,140	19,451,566	1,682,040	8.65	8.04 - 9.25	15,438	18,431,983	1,550,245	8.41	7.81 - 9.01
2018	15,887	19,781,106	1,860,006	9.4	8.83 - 9.98	15,188	18,560,177	1,688,811	9.1	8.52 - 9.68
2019	16,082	20,108,254	2,124,142	10.56	9.93 - 11.2	15,333	19,011,660	1,911,392	10.05	9.43 - 10.68
2020	15,676	20,298,824	2,087,133	10.28	9.63 - 10.94	15,044	19,176,063	1,869,290	9.75	9.16 - 10.33
2021	15,299	20,373,462	1,905,404	9.35	8.72 - 9.99	14,684	19,336,293	1,747,990	9.04	8.39 - 9.69
2022	14,814	20,791,738	2,031,921	9.77	9.1 - 10.44	14,272	19,811,975	1,862,988	9.4	8.74 - 10.06
2023	14,917	21,437,023	2,567,249	11.98	11.24 - 12.71	14,224	19,343,696	2,295,619	11.87	11.15 - 12.58

Appendix B.5

Prevalence of each hardship item in Australia from 2001 to 2023.

- FH Item 1 - *Could not pay electricity, gas, or telephone bills on time.*
- FH Item 2 – *Asked for financial help from friends or family.*
- FH Item 3 – *Could not pay the mortgage or rent on time.*
- FH Item 4 – *Pawned or sold something.*
- FH Item 5 – *Was unable to heat home.*
- FH Item 6 – *Went without meals.*
- FH Item 7 – *Asked for help from welfare/community organisations.*

Year	FH Item	n	n (weighted)	FH n (weighted)	FH % (weighted)	FH 95% CI
2001	FH1	13,058	14,923,779	2,688,594	18.34	17.61 - 19.08
2001	FH2	13,058	14,923,779	2,446,540	16.73	16 - 17.45
2001	FH3	13,058	14,923,779	1,279,724	8.82	8.26 - 9.37
2001	FH4	13,058	14,923,779	919,325	6.31	5.85 - 6.76
2001	FH5	13,058	14,923,779	528,382	3.63	3.27 - 3.99
2001	FH6	13,058	14,923,779	664,903	4.56	4.16 - 4.96
2001	FH7	13,058	14,923,779	772,356	5.29	4.85 - 5.74
2002	FH1	12,130	15,133,844	2,369,339	15.88	15.07 - 16.69
2002	FH2	12,130	15,133,844	2,015,873	13.51	12.73 - 14.28
2002	FH3	12,130	15,133,844	1,181,277	7.96	7.3 - 8.63
2002	FH4	12,130	15,133,844	740,828	4.98	4.51 - 5.46
2002	FH5	12,130	15,133,844	409,023	2.75	2.43 - 3.07
2002	FH6	12,130	15,133,844	539,829	3.62	3.19 - 4.06
2002	FH7	12,130	15,133,844	591,226	3.97	3.48 - 4.46
2003	FH1	11,747	15,347,574	2,265,178	15.01	14.15 - 15.87
2003	FH2	11,747	15,347,574	2,203,845	14.61	13.72 - 15.5
2003	FH3	11,747	15,347,574	1,086,200	7.24	6.59 - 7.9
2003	FH4	11,747	15,347,574	781,399	5.2	4.64 - 5.76
2003	FH5	11,747	15,347,574	414,105	2.76	2.3 - 3.22
2003	FH6	11,747	15,347,574	585,141	3.9	3.38 - 4.41
2003	FH7	11,747	15,347,574	627,248	4.18	3.57 - 4.78
2004	FH1	11,397	15,552,868	2,140,730	14.02	13.18 - 14.85
2004	FH2	11,397	15,552,868	2,025,002	13.31	12.51 - 14.12
2004	FH3	11,397	15,552,868	1,008,102	6.67	6.04 - 7.3
2004	FH4	11,397	15,552,868	669,157	4.41	3.95 - 4.88
2004	FH5	11,397	15,552,868	354,741	2.34	2.01 - 2.68
2004	FH6	11,397	15,552,868	553,827	3.66	3.16 - 4.16
2004	FH7	11,397	15,552,868	507,173	3.34	2.89 - 3.8
2005	FH1	11,465	15,786,018	2,074,100	13.31	12.43 - 14.18
2005	FH2	11,465	15,786,018	2,107,980	13.51	12.6 - 14.42
2005	FH3	11,465	15,786,018	1,088,950	7.02	6.31 - 7.72
2005	FH4	11,465	15,786,018	642,667	4.13	3.66 - 4.6
2005	FH5	11,465	15,786,018	345,881	2.22	1.81 - 2.64
2005	FH6	11,465	15,786,018	473,354	3.04	2.63 - 3.46
2005	FH7	11,465	15,786,018	529,422	3.4	2.98 - 3.83
2006	FH1	11,688	16,057,442	1,935,477	12.28	11.45 - 13.11
2006	FH2	11,688	16,057,442	1,883,832	11.98	11.11 - 12.84
2006	FH3	11,688	16,057,442	958,036	6.12	5.49 - 6.74
2006	FH4	11,688	16,057,442	574,685	3.66	3.2 - 4.12
2006	FH5	11,688	16,057,442	258,114	1.65	1.39 - 1.91
2006	FH6	11,688	16,057,442	458,766	2.92	2.56 - 3.29
2006	FH7	11,688	16,057,442	479,045	3.05	2.64 - 3.47
2007	FH1	11,381	16,379,640	2,016,454	12.59	11.67 - 13.51
2007	FH2	11,381	16,379,640	2,085,089	13.02	12.07 - 13.97
2007	FH3	11,381	16,379,640	1,088,931	6.83	6.03 - 7.64

2007	FH4	11,381	16,379,640	679,722	4.26	3.64 - 4.88
2007	FH5	11,381	16,379,640	325,970	2.04	1.7 - 2.38
2007	FH6	11,381	16,379,640	535,313	3.35	2.79 - 3.91
2007	FH7	11,381	16,379,640	495,621	3.1	2.56 - 3.64
2008	FH1	11,193	16,750,326	1,733,853	11.25	10.41 - 12.08
2008	FH2	11,193	16,750,326	1,770,083	11.49	10.65 - 12.34
2008	FH3	11,193	16,750,326	855,472	5.57	4.99 - 6.16
2008	FH4	11,193	16,750,326	573,638	3.74	3.17 - 4.31
2008	FH5	11,193	16,750,326	352,657	2.31	1.92 - 2.69
2008	FH6	11,193	16,750,326	528,808	3.45	2.94 - 3.97
2008	FH7	11,193	16,750,326	511,265	3.34	2.74 - 3.94
2009	FH1	11,563	17,105,835	1,964,306	11.71	10.84 - 12.58
2009	FH2	11,563	17,105,835	2,103,520	12.55	11.68 - 13.42
2009	FH3	11,563	17,105,835	1,063,860	6.37	5.64 - 7.1
2009	FH4	11,563	17,105,835	739,311	4.42	3.82 - 5.01
2009	FH5	11,563	17,105,835	401,035	2.4	1.93 - 2.86
2009	FH6	11,563	17,105,835	666,378	3.98	3.36 - 4.6
2009	FH7	11,563	17,105,835	665,131	3.97	3.41 - 4.53
2010	FH1	12,052	17,371,743	0	0	0 - 0
2010	FH2	12,052	17,371,743	0	0	0 - 0
2010	FH3	12,052	17,371,743	0	0	0 - 0
2010	FH4	12,052	17,371,743	0	0	0 - 0
2010	FH5	12,052	17,371,743	0	0	0 - 0
2010	FH6	12,052	17,371,743	0	0	0 - 0
2010	FH7	12,052	17,371,743	0	0	0 - 0
2011	FH1	15,366	17,641,853	2,340,362	13.44	12.65 - 14.23
2011	FH2	15,366	17,641,853	2,327,762	13.38	12.6 - 14.16
2011	FH3	15,366	17,641,853	1,203,711	6.95	6.29 - 7.61
2011	FH4	15,366	17,641,853	888,800	5.13	4.7 - 5.55
2011	FH5	15,366	17,641,853	736,485	4.24	3.74 - 4.75
2011	FH6	15,366	17,641,853	617,290	3.55	3.12 - 3.99
2011	FH7	15,366	17,641,853	711,769	4.1	3.61 - 4.59
2012	FH1	15,389	17,955,273	2,176,404	12.88	12.12 - 13.63
2012	FH2	15,389	17,955,273	2,163,827	12.8	12.06 - 13.55
2012	FH3	15,389	17,955,273	1,075,061	6.39	5.85 - 6.93
2012	FH4	15,389	17,955,273	834,320	4.95	4.52 - 5.39
2012	FH5	15,389	17,955,273	564,714	3.35	3.01 - 3.69
2012	FH6	15,389	17,955,273	562,740	3.34	2.92 - 3.75
2012	FH7	15,389	17,955,273	619,451	3.67	3.3 - 4.05
2013	FH1	15,360	18,257,488	2,191,269	12.19	11.46 - 12.92
2013	FH2	15,360	18,257,488	2,120,394	11.8	11.03 - 12.56
2013	FH3	15,360	18,257,488	1,020,351	5.71	5.18 - 6.23
2013	FH4	15,360	18,257,488	884,237	4.93	4.48 - 5.37
2013	FH5	15,360	18,257,488	553,975	3.09	2.74 - 3.44
2013	FH6	15,360	18,257,488	626,642	3.49	3.14 - 3.84
2013	FH7	15,360	18,257,488	673,909	3.75	3.34 - 4.17
2014	FH1	15,595	18,529,494	2,162,973	12.11	11.45 - 12.77
2014	FH2	15,595	18,529,494	2,361,253	13.23	12.44 - 14.02
2014	FH3	15,595	18,529,494	1,021,424	5.75	5.27 - 6.23
2014	FH4	15,595	18,529,494	925,633	5.2	4.74 - 5.66
2014	FH5	15,595	18,529,494	546,921	3.08	2.72 - 3.43
2014	FH6	15,595	18,529,494	684,027	3.84	3.41 - 4.27
2014	FH7	15,595	18,529,494	672,025	3.78	3.39 - 4.16
2015	FH1	15,513	18,803,944	2,224,162	11.96	11.21 - 12.7
2015	FH2	15,513	18,803,944	2,177,709	11.7	10.96 - 12.44
2015	FH3	15,513	18,803,944	1,007,907	5.44	4.88 - 5.99
2015	FH4	15,513	18,803,944	1,011,755	5.44	4.94 - 5.95
2015	FH5	15,513	18,803,944	558,046	3.01	2.66 - 3.35
2015	FH6	15,513	18,803,944	638,041	3.44	3.08 - 3.8
2015	FH7	15,513	18,803,944	727,659	3.92	3.5 - 4.34

2016	FH1	16,253	19,120,187	2,089,182	11.14	10.44 - 11.85
2016	FH2	16,253	19,120,187	2,102,206	11.22	10.49 - 11.95
2016	FH3	16,253	19,120,187	1,106,502	5.92	5.31 - 6.52
2016	FH4	16,253	19,120,187	989,324	5.29	4.81 - 5.76
2016	FH5	16,253	19,120,187	521,670	2.79	2.47 - 3.1
2016	FH6	16,253	19,120,187	648,411	3.46	3.11 - 3.81
2016	FH7	16,253	19,120,187	655,962	3.5	3.13 - 3.87
2017	FH1	16,140	19,451,566	1,937,460	10.63	9.95 - 11.3
2017	FH2	16,140	19,451,566	1,961,977	10.74	10.03 - 11.46
2017	FH3	16,140	19,451,566	976,815	5.38	4.84 - 5.92
2017	FH4	16,140	19,451,566	826,659	4.54	4.1 - 4.98
2017	FH5	16,140	19,451,566	537,701	2.95	2.61 - 3.3
2017	FH6	16,140	19,451,566	622,194	3.42	3.03 - 3.8
2017	FH7	16,140	19,451,566	609,693	3.35	2.92 - 3.78
2018	FH1	15,887	19,781,106	2,150,458	11.26	10.46 - 12.05
2018	FH2	15,887	19,781,106	2,273,093	11.9	11.14 - 12.67
2018	FH3	15,887	19,781,106	1,111,464	5.85	5.21 - 6.49
2018	FH4	15,887	19,781,106	970,494	5.09	4.67 - 5.52
2018	FH5	15,887	19,781,106	607,007	3.19	2.82 - 3.56
2018	FH6	15,887	19,781,106	738,441	3.88	3.5 - 4.26
2018	FH7	15,887	19,781,106	648,874	3.41	3.06 - 3.76
2019	FH1	16,082	20,108,254	2,039,183	10.32	9.65 - 11
2019	FH2	16,082	20,108,254	2,324,213	11.76	11.08 - 12.45
2019	FH3	16,082	20,108,254	1,137,436	5.78	5.22 - 6.33
2019	FH4	16,082	20,108,254	1,099,739	5.58	5.1 - 6.06
2019	FH5	16,082	20,108,254	640,683	3.25	2.89 - 3.61
2019	FH6	16,082	20,108,254	844,437	4.28	3.87 - 4.69
2019	FH7	16,082	20,108,254	740,872	3.76	3.38 - 4.13
2020	FH1	15,676	20,298,824	2,125,008	10.64	9.87 - 11.4
2020	FH2	15,676	20,298,824	1,703,820	8.52	7.91 - 9.13
2020	FH3	15,676	20,298,824	1,356,051	6.8	6.18 - 7.43
2020	FH4	15,676	20,298,824	1,016,144	5.09	4.62 - 5.56
2020	FH5	15,676	20,298,824	603,413	3.02	2.64 - 3.4
2020	FH6	15,676	20,298,824	645,243	3.23	2.86 - 3.59
2020	FH7	15,676	20,298,824	952,161	4.87	4.39 - 5.34
2021	FH1	15,299	20,373,462	1,986,100	9.98	9.31 - 10.66
2021	FH2	15,299	20,373,462	1,780,944	8.96	8.34 - 9.59
2021	FH3	15,299	20,373,462	1,245,238	6.27	5.75 - 6.8
2021	FH4	15,299	20,373,462	938,469	4.73	4.28 - 5.17
2021	FH5	15,299	20,373,462	543,101	2.74	2.41 - 3.06
2021	FH6	15,299	20,373,462	677,650	3.41	3.07 - 3.75
2021	FH7	15,299	20,373,462	786,096	3.96	3.5 - 4.42
2022	FH1	14,814	20,791,738	2,024,968	9.84	9.08 - 10.6
2022	FH2	14,814	20,791,738	1,957,286	9.51	8.88 - 10.14
2022	FH3	14,814	20,791,738	1,208,981	5.89	5.24 - 6.53
2022	FH4	14,814	20,791,738	1,073,220	5.22	4.69 - 5.75
2022	FH5	14,814	20,791,738	690,231	3.36	2.95 - 3.77
2022	FH6	14,814	20,791,738	813,208	3.95	3.54 - 4.37
2022	FH7	14,814	20,791,738	718,438	3.49	3.11 - 3.88
2023	FH1	14,917	21,437,023	2,368,276	11.23	10.46 - 11.99
2023	FH2	14,917	21,437,023	2,438,849	11.57	10.82 - 12.32
2023	FH3	14,917	21,437,023	1,424,455	6.77	6.12 - 7.42
2023	FH4	14,917	21,437,023	1,306,924	6.2	5.67 - 6.73
2023	FH5	14,917	21,437,023	897,683	4.26	3.76 - 4.76
2023	FH6	14,917	21,437,023	1,091,768	5.18	4.68 - 5.69
2023	FH7	14,917	21,437,023	875,440	4.16	3.71 - 4.6

Appendix B.6

Multivariable mixed-effects logistic regression models, estimating how the likelihood of experiencing cashflow problems, and deprivation has evolved over time, by sex.

	Cashflow Problems		Deprivation	
	Model 1		Model 2	
Characteristic	**OR**	**95% CI**	**OR**	**95% CI**
Sex				
Male	—	—	—	—
Female	1.19	**1.10, 1.28**	0.88	**0.80, 0.97**
Age Category				
15-19	1.16	**1.04, 1.30**	1.57	**1.38, 1.79**
20-29	—	**—**	—	**—**
30-39	0.61	**0.58, 0.64**	0.78	**0.73, 0.83**
40-49	0.46	**0.43, 0.50**	0.64	**0.58, 0.71**
50-59	0.31	**0.28, 0.35**	0.56	**0.49, 0.64**
60-69	0.20	**0.17, 0.23**	0.42	**0.36, 0.50**
70+	0.19	**0.16, 0.23**	0.38	**0.30, 0.47**
Birth Cohort				
1900-1929	0.22	**0.17, 0.28**	0.26	**0.18, 0.35**
1930-1949	0.31	**0.26, 0.36**	0.34	**0.28, 0.42**
1950-1969	0.63	**0.57, 0.69**	0.59	**0.52, 0.67**
1970-1989	—	**—**	—	**—**
1990-2009	0.83	**0.76, 0.91**	1.24	**1.09, 1.40**
Time				
01-06	—	—	—	—
07-12	0.71	**0.67, 0.75**	0.83	**0.77, 0.90**
13-18	0.57	**0.53, 0.61**	0.80	**0.74, 0.87**
19-23	0.45	**0.42, 0.49**	0.78	**0.71, 0.86**
Residing with Parent (15-19)				
Yes	—	—	—	—
No	6.17	5.46, 6.98	5.24	**4.53, 6.06**
Residing with Parent (20-29)				
Yes	—	—	—	—
No	2.07	1.93, 2.22	1.78	**1.62, 1.95**
*Sex * Time*				
Female * 07-12	1.06	0.99, 1.14	1.17	**1.06, 1.29**
Female * 13-18	1.07	0.99, 1.15	1.22	**1.11, 1.34**
Female * 19-23	1.13	**1.04, 1.22**	1.32	**1.19, 1.46**

Appendix B.7

Multivariable mixed-effects logistic regression models, estimating how the likelihood of experiencing cashflow problems, and deprivation has evolved over time, by age.

	Cashflow Problems		Deprivation	
	Model 3		Model 4	
Characteristic	**OR**	**95% CI**	**OR**	**95% CI**
Sex				
Male	—	—	—	—
Female	1.26	**1.19, 1.34**	1.03	0.95, 1.11
Age Category				
15-19	0.95	0.82, 1.10	1.40	**1.17, 1.67**
20-29	—	—	—	—
30-39	0.56	**0.51, 0.62**	0.73	**0.64, 0.83**
40-49	0.40	**0.35, 0.45**	0.54	**0.46, 0.64**
50-59	0.28	**0.24, 0.32**	0.47	**0.38, 0.57**
60-69	0.15	**0.12, 0.18**	0.33	**0.26, 0.43**
70+	0.08	**0.07, 0.10**	0.32	**0.24, 0.44**
Birth Cohort				
1900-1929	0.36	**0.28, 0.47**	0.26	**0.18, 0.37**
1930-1949	0.33	**0.28, 0.40**	0.36	**0.29, 0.45**
1950-1969	0.61	**0.55, 0.68**	0.61	**0.53, 0.70**
1970-1989	—	—	—	—
1990-2009	1.00	0.90, 1.11	1.28	**1.11, 1.47**
Time				
01-06	—	—	—	—
07-12	0.61	**0.56, 0.66**	0.78	**0.69, 0.87**
13-18	0.44	**0.40, 0.49**	0.78	**0.69, 0.89**
19-23	0.32	**0.28, 0.36**	0.77	**0.66, 0.89**
Residing with Parent (15-19)				
Yes	—	—	—	—
No	6.32	**5.59, 7.14**	5.28	**4.56, 6.10**
Residing with Parent (20-29)				
Yes	—	—	—	—
No	2.14	**2.00, 2.30**	1.79	**1.63, 1.96**
*Age Category * Time*				
15-19 * 07-12	1.08	0.92, 1.27	1.10	0.90, 1.36
30-39 * 07-12	1.11	0.98, 1.26	1.07	0.90, 1.25
40-49 * 07-12	1.28	**1.13, 1.44**	1.19	**1.01, 1.40**
50-59 * 07-12	1.25	**1.09, 1.43**	1.33	**1.11, 1.61**
60-69 * 07-12	1.51	**1.28, 1.78**	1.47	**1.18, 1.83**
70+ * 07-12	2.03	**1.70, 2.44**	1.38	**1.09, 1.76**
15-19 * 13-18	1.17	1.00, 1.38	1.08	0.88, 1.32
30-39 * 13-18	1.28	**1.12, 1.46**	1.08	0.91, 1.28
40-49 * 13-18	1.43	**1.25, 1.65**	1.31	**1.09, 1.57**
50-59 * 13-18	1.28	**1.10, 1.49**	1.15	0.94, 1.41
60-69 * 13-18	1.54	**1.29, 1.85**	1.32	**1.04, 1.67**
70+ * 13-18	2.32	**1.91, 2.82**	1.18	0.91, 1.52
15-19 * 19-23	1.44	**1.19, 1.73**	1.36	**1.09, 1.71**
30-39 * 19-23	1.33	**1.16, 1.53**	1.17	0.97, 1.39
40-49 * 19-23	1.53	**1.30, 1.81**	1.28	**1.03, 1.59**
50-59 * 19-23	1.55	**1.30, 1.85**	1.31	**1.04, 1.65**
60-69 * 19-23	1.88	**1.53, 2.31**	1.29	0.99, 1.70
70+ * 19-23	3.48	**2.80, 4.32**	1.13	0.85, 1.49

Appendix B.8

Model comparisons for cashflow problems and deprivation over time.

1. Cashflow Problems

Sex x Time

Model Comparison 1a - Sex vs Sex x Time

Models	Parameters	AIC	BIC	LogLik	Deviance	Chi Sq	Df	p-value
Sex	3	229,021.90	229,053.80	-114,508.00	229,015.90			
Sex x Time	9	226,920.20	227,015.80	-113,451.10	226,902.20	2,113.71	6	**<0.001**

Model Comparison 1b - Sex x Time vs Sex x Time + Covariates

Models	Parameters	AIC	BIC	LogLik	Deviance	Chi Sq	Df	p-value
Sex x Time	9	226,920.20	227,015.80	-113,451.10	226,902.20			
Sex x Time + Cov.	21	220,755.90	220,978.80	-110,357.00	220,713.90	6,188.32	12	**<0.001**

Age x Time

Model Comparison 2a - Age vs. Age x Time

Models	Parameters	AIC	BIC	LogLik	Deviance	Chi Sq	Df	p-value
Age	8	222,776.80	222,861.80	-111,380.40	222,760.80			
Age x Time	29	222,063.20	222,371.00	-111,002.60	222,005.20	755.67	21	**<0.001**

Model Comparison 2b - Age x Time vs Age x Time + Covariates

Models	Parameters	AIC	BIC	LogLik	Deviance	Chi Sq	Df	p-value
Age x Time	29	222,063.20	222,371.00	-111,002.60	222,005.20			
Age x Time + Cov.	36	220,645.80	221,028.00	-110,286.90	220,573.80	1,431.33	7	**<0.001**

2. Deprivation

Sex x Time

Model Comparison 3a - Sex vs Sex x Time

Models	Parameters	AIC	BIC	LogLik	Deviance	Chi Sq	Df	p-value
Sex	3	151,601.70	151,633.50	-75,797.85	151,595.70			
Sex x Time	9	151,566.00	151,661.50	-75,773.99	151,548.00	47.73	6	**<0.001**

Model Comparison 3b - Sex x Time vs Sex x Time + Covariates

Models	Parameters	AIC	BIC	LogLik	Deviance	Chi Sq	Df	p-value
Sex x Time	9	151,566.00	151,661.50	-75,773.99	151,548.00			
Sex x Time + Cov.	21	149,517.40	149,740.30	-74,737.70	149,475.40	2,072.59	12	**<0.001**

Age x Time

Model Comparison 4a - Age vs. Age x Time

Models	Parameters	AIC	BIC	LogLik	Deviance	Chi Sq	Df	p-value
Age	8	150,293.60	150,378.50	-75,138.79	150,277.60			
Age x Time	29	150,198.40	150,506.20	-75,070.19	150,140.40	137.20	21	**<0.001**

Model Comparison 4b - Age x Time vs Age x Time + Covariates

Models	Parameters	AIC	BIC	LogLik	Deviance	Chi Sq	Df	p-value
Age x Time	29	150,198.40	150,506.20	-75,070.19	150,140.40			
Age x Time + Cov.	36	149,532.70	149,914.80	-74,730.33	149,460.70	679.73	7	**<0.001**

Appendix B.9

Mixed-effects logistic regression models examining the association between key sociodemographic/health factors and their contribution to the significantly lower odds of deprivation observed in females.

	Model 1.1		**Model 1.2**		**Model 1.3**		**Model 1.4**		**Model 1.5**		**Model 1.6**		**Model 1.7**		**Model 1.8**		**Model 1.9**		**Model 1.10**		**Model 1.11**	
Characteristic	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**	**OR[1]**	**95% CI[1]**
Sex																						
Male	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Female	1.05	0.97, 1.14	1.06	0.97, 1.14	1.06	0.97, 1.14	1.06	0.98, 1.14	1.09	**1.01, 1.18**	0.87	**0.80, 0.93**	0.9	**0.84, 0.97**	1.01	0.94, 1.08	0.92	**0.85, 0.98**	0.89	**0.83, 0.95**	0.84	**0.79, 0.90**
Age Category																						
15-19	0.55	**0.52, 0.59**	0.53	**0.50, 0.57**	0.53	**0.49, 0.57**	0.53	**0.49, 0.57**	0.43	**0.40, 0.47**	0.37	**0.34, 0.40**	0.33	**0.31, 0.36**	0.45	**0.42, 0.49**	0.33	**0.31, 0.36**	0.34	**0.31, 0.37**	0.36	**0.33, 0.39**
20-29	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
30-39	0.77	**0.73, 0.81**	0.84	**0.79, 0.89**	0.84	**0.79, 0.90**	0.84	**0.78, 0.89**	0.88	**0.82, 0.94**	0.86	**0.80, 0.92**	0.89	**0.83, 0.95**	0.86	**0.81, 0.92**	0.89	**0.84, 0.96**	0.87	**0.82, 0.93**	0.86	**0.80, 0.92**
40-49	0.54	**0.51, 0.58**	0.67	**0.62, 0.72**	0.68	**0.62, 0.75**	0.67	**0.61, 0.74**	0.7	**0.63, 0.77**	0.71	**0.64, 0.78**	0.73	**0.66, 0.80**	0.7	**0.63, 0.77**	0.74	**0.67, 0.81**	0.68	**0.62, 0.75**	0.7	**0.63, 0.77**
50-59	0.4	**0.37, 0.43**	0.56	**0.51, 0.62**	0.58	**0.51, 0.66**	0.57	**0.50, 0.65**	0.59	**0.51, 0.67**	0.56	**0.49, 0.64**	0.57	**0.50, 0.65**	0.61	**0.54, 0.70**	0.61	**0.53, 0.69**	0.52	**0.46, 0.60**	0.58	**0.51, 0.66**
60-69	0.26	**0.24, 0.28**	0.41	**0.37, 0.46**	0.43	**0.36, 0.51**	0.42	**0.35, 0.49**	0.42	**0.35, 0.49**	0.31	**0.27, 0.37**	0.32	**0.27, 0.38**	0.37	**0.31, 0.44**	0.31	**0.26, 0.37**	0.26	**0.22, 0.30**	0.33	**0.28, 0.38**
70+	0.18	**0.16, 0.20**	0.35	**0.30, 0.41**	0.37	**0.30, 0.46**	0.36	**0.29, 0.44**	0.34	**0.27, 0.42**	0.23	**0.19, 0.28**	0.23	**0.18, 0.28**	0.25	**0.20, 0.31**	0.19	**0.16, 0.24**	0.15	**0.12, 0.19**	0.21	**0.17, 0.26**
Birth Cohort																						
1900-1929			0.3	**0.23, 0.40**	0.28	**0.20, 0.39**	0.29	**0.21, 0.40**	0.25	**0.18, 0.34**	0.25	**0.18, 0.33**	0.23	**0.17, 0.31**	0.23	**0.17, 0.31**	0.2	**0.15, 0.28**	0.17	**0.13, 0.23**	0.23	**0.17, 0.30**
1930-1949			0.39	**0.33, 0.46**	0.37	**0.30, 0.45**	0.38	**0.31, 0.46**	0.35	**0.29, 0.42**	0.32	**0.27, 0.39**	0.31	**0.26, 0.38**	0.33	**0.28, 0.40**	0.3	**0.25, 0.36**	0.27	**0.22, 0.32**	0.35	**0.29, 0.42**
1950-1969			0.63	**0.56, 0.71**	0.62	**0.54, 0.70**	0.63	**0.55, 0.71**	0.61	**0.54, 0.69**	0.63	**0.56, 0.72**	0.62	**0.55, 0.70**	0.63	**0.56, 0.71**	0.62	**0.55, 0.70**	0.6	**0.54, 0.68**	0.67	**0.60, 0.75**
1970-1989			—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
1990-2009			1.07	0.96, 1.19	1.09	0.96, 1.23	1.08	0.96, 1.21	0.98	0.87, 1.10	0.99	0.88, 1.11	0.92	0.83, 1.03	1.04	0.93, 1.16	0.94	0.84, 1.05	0.98	0.88, 1.09	0.86	**0.78, 0.96**
Time Block																						
01-06					—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
07-12					0.92	**0.87, 0.97**	0.92	**0.87, 0.97**	0.95	0.90, 1.01	0.94	**0.89, 0.99**	0.96	0.91, 1.01	1.12	**1.07, 1.19**	1.12	**1.06, 1.18**	1.1	**1.05, 1.17**	1.13	**1.07, 1.19**
13-18					0.93	**0.87, 0.99**	0.93	**0.87, 0.99**	1	0.93, 1.06	0.92	**0.87, 0.98**	0.97	0.91, 1.03	1.17	**1.09, 1.24**	1.16	**1.09, 1.23**	1.12	**1.05, 1.19**	1.13	**1.06, 1.20**
19-23					0.97	0.89, 1.05	0.95	0.88, 1.03	1.06	0.98, 1.15	0.99	0.91, 1.07	1.07	0.98, 1.15	1.3	**1.20, 1.41**	1.33	**1.23, 1.45**	1.28	**1.18, 1.38**	1.2	**1.11, 1.30**
SEIFA																						
5							—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
4							1.34	**1.24, 1.44**	1.25	**1.16, 1.35**	1.3	**1.20, 1.40**	1.23	**1.14, 1.33**	1.17	**1.09, 1.26**	1.11	**1.03, 1.20**	1.08	**1.00, 1.17**	1.1	**1.02, 1.19**
3							1.64	**1.51, 1.77**	1.47	**1.36, 1.59**	1.59	**1.47, 1.72**	1.46	**1.35, 1.57**	1.35	**1.25, 1.46**	1.26	**1.16, 1.36**	1.22	**1.13, 1.32**	1.26	**1.17, 1.36**
2							1.89	**1.75, 2.05**	1.67	**1.55, 1.81**	1.79	**1.66, 1.93**	1.62	**1.50, 1.75**	1.48	**1.37, 1.59**	1.33	**1.23, 1.44**	1.28	**1.19, 1.39**	1.32	**1.22, 1.42**
1							2.53	**2.34, 2.74**	2.2	**2.03, 2.39**	2.32	**2.14, 2.51**	2.07	**1.92, 2.24**	1.86	**1.72, 2.01**	1.63	**1.51, 1.76**	1.55	**1.44, 1.68**	1.6	**1.48, 1.72**
Education																						
Postgrad									—	—			—	—			—	—	—	—	—	—
Undergrad									1.4	**1.18, 1.64**			1.31	**1.12, 1.54**			1.2	**1.03, 1.41**	1.18	**1.01, 1.38**	1.19	**1.02, 1.39**
Diploma/Vocational									3.26	**2.76, 3.84**			2.74	**2.33, 3.21**			2.14	**1.83, 2.51**	2.01	**1.72, 2.35**	2.05	**1.75, 2.39**
Year 12									3.39	**2.86, 4.01**			2.61	**2.22, 3.08**			1.89	**1.61, 2.23**	1.78	**1.52, 2.10**	1.77	**1.51, 2.08**
Year 11 or below									4.06	**3.43, 4.81**			2.88	**2.44, 3.40**			2.08	**1.77, 2.45**	1.91	**1.62, 2.24**	1.91	**1.63, 2.25**
Employment																						
Full Time											—	—	—	—			—	—	—	—	—	—
Part Time											2.01	**1.91, 2.12**	1.93	**1.83, 2.03**			1.6	**1.52, 1.69**	1.57	**1.49, 1.66**	1.54	**1.46, 1.62**
Unemployed											5.47	**5.08, 5.88**	5.25	**4.88, 5.65**			3.97	**3.69, 4.28**	3.85	**3.58, 4.15**	3.58	**3.33, 3.86**
Not in labour force											3.43	**3.24, 3.63**	3.22	**3.05, 3.41**			2.32	**2.19, 2.46**	2.12	**2.00, 2.25**	2.07	**1.96, 2.20**
Income Quintile																						
5															—	—	—	—	—	—	—	—
4															1.76	**1.65, 1.89**	1.67	**1.55, 1.79**	1.65	**1.54, 1.77**	1.62	**1.51, 1.73**
3															3.01	**2.80, 3.22**	2.61	**2.44, 2.80**	2.59	**2.41, 2.77**	2.53	**2.36, 2.71**
2															5.33	**4.97, 5.73**	4.18	**3.89, 4.49**	4.11	**3.82, 4.41**	4.01	**3.73, 4.30**
1															9.02	**8.37, 9.73**	6.47	**5.99, 6.99**	6.29	**5.82, 6.79**	6.1	**5.65, 6.59**
Physical Functioning (SF-36)																						
91-100																			—	—		
81-90																			1.44	**1.36, 1.51**		
71-80																			1.69	**1.58, 1.81**		
61-70																			1.94	**1.80, 2.10**		
51-60																			2.02	**1.85, 2.20**		
41-50																			2.24	**2.06, 2.43**		
31-40																			2.43	**2.21, 2.68**		
21-30																			2.55	**2.31, 2.83**		
11-20																			2.73	**2.44, 3.06**		
0-10																			2.41	**2.15, 2.70**		
Mental Health (SF-36)																						
91-100																					—	—
81-90																					1.36	**1.26, 1.46**
71-80																					2.05	**1.91, 2.20**
61-70																					2.87	**2.66, 3.11**
51-60																					3.79	**3.51, 4.09**
41-50																					5.1	**4.67, 5.57**
31-40																					6.12	**5.58, 6.71**
21-30																					8.01	**7.09, 9.05**
11-20																					10.4	**9.02, 11.9**
0-10																					16.1	**12.8, 20.3**

[1] OR = Odds Ratio, CI = Confidence Interval

Appendix C – Supplementary Material for Chapter 4

Appendix C.1

Model fit comparison statistics – Satorra-Bentler χ^2 difference tests.

Model	χ^2	df	AIC	BIC	$\Delta\chi^2$	Δdf	p-value
1. Unconstrained	393.03	31	316,962	317,223	—	—	—
2. Fully Constrained	438.75	47	316,976	317,114	21.919	16	0.1458

Model	χ^2	df	AIC	BIC	$\Delta\chi^2$	Δdf	p-value
3. Part Constrained	410.72	43	316,956	317,125	—	—	—
2. Fully Constrained	438.75	47	316,976	317,114	16.09	4	**0.0029**

Appendix C.2

Model output for 1. Unconstrained RI-CLPM, and 2. Fully Constrained RI-CLPM.

Standardised parameter estimates for random-intercept cross-lagged panel model – Unconstrained.

			1. Unconstrained RI-CLPM		
Outcome	**Predictor**	**Parameter**	**Estimate (β)**	**SE**	**p-value**
Autoregressive Terms					
FH - W20	FH - W19	a1	0.135	0.018	**<0.001**
FH - W21	FH - W20	a2	0.111	0.016	**<0.001**
FH - W22	FH - W21	a3	0.110	0.018	**<0.001**
FH - W23	FH - W22	a4	0.115	0.018	**<0.001**
SF-36 MH - W20	SF-36 MH - W19	a5	0.126	0.009	**<0.001**
SF-36 MH - W21	SF-36 MH - W20	a6	0.127	0.008	**<0.001**
SF-36 MH - W22	SF-36 MH - W21	a7	0.113	0.008	**<0.001**
SF-36 MH - W23	SF-36 MH - W22	a8	0.117	0.009	**<0.001**
Cross-lagged Terms					
FH - W20	SF-36 MH - W19	b1	-0.008	0.009	0.401
FH - W21	SF-36 MH - W20	b2	-0.001	0.010	0.890
FH - W22	SF-36 MH - W21	b3	-0.004	0.009	0.657
FH - W23	SF-36 MH - W22	b4	-0.013	0.010	0.184
SF-36 MH - W20	FH - W19	b5	0.014	0.009	0.120
SF-36 MH - W21	FH - W20	b6	0.017	0.008	**0.038**
SF-36 MH - W22	FH - W21	b7	0.016	0.008	**0.049**
SF-36 MH - W23	FH - W22	b8	0.021	0.009	**0.022**
Covariance Terms					
FH - W19	SF-36 MH - W19	e1	-0.041	0.007	**<0.001**
FH - W20	SF-36 MH - W20	e2	-0.018	0.006	**0.003**
FH - W21	SF-36 MH - W21	e3	-0.020	0.005	**<0.001**
FH - W22	SF-36 MH - W22	e4	-0.025	0.006	**<0.001**
FH - W23	SF-36 MH - W23	e5	-0.044	0.006	**<0.001**
RI - FH	RI - MH		-0.216	0.010	**<0.001**
Variance Terms					
RI - FH	RI - FH		0.467	0.020	**<0.001**
RI - MH	RI - MH		0.545	0.011	**<0.001**
FH - W19	FH - W19		0.495	0.018	**<0.001**
FH - W20	FH - W20		0.471	0.018	**<0.001**
FH - W21	FH - W21		0.450	0.018	**<0.001**
FH - W22	FH - W22		0.431	0.018	**<0.001**
FH - W23	FH - W23		0.454	0.018	**<0.001**
SF-36 MH - W19	SF-36 MH - W19		0.419	0.009	**<0.001**
SF-36 MH - W20	SF-36 MH - W20		0.347	0.007	**<0.001**
SF-36 MH - W21	SF-36 MH - W21		0.319	0.007	**<0.001**
SF-36 MH - W22	SF-36 MH - W22		0.314	0.007	**<0.001**
SF-36 MH - W23	SF-36 MH - W23		0.348	0.008	**<0.001**

Standardised parameter estimates for random-intercept cross-lagged panel model – Fully Constrained.

		2. Fully Constrained RI-CLPM			
Outcome	**Predictor**	**Parameter**	**Estimate (β)**	**SE**	**p-value**
Autoregressive Terms					
FH_t	FH_{t-1}	a1	0.117	0.012	**<0.001**
MH_t	MH_{t-1}	a5	0.121	0.007	**<0.001**
Cross-lagged Terms					
FH_t	MH_{t-1}	b1	-0.008	0.006	0.244
MH_t	FH_{t-1}	b5	0.016	0.005	**0.004**
Covariance Terms					
FH	MH	e1	-0.029	0.003	**<0.001**
RI - FH	RI - MH		-0.216	0.009	**<0.001**
Variance Terms					
RI - FH	RI - FH		0.468	0.020	**<0.001**
RI - MH	RI - MH		0.545	0.011	**<0.001**
FH - W19	FH - W19		0.488	0.017	**<0.001**
FH - W20	FH - W20		0.475	0.018	**<0.001**
FH - W21	FH - W21		0.454	0.018	**<0.001**
FH - W22	FH - W22		0.432	0.017	**<0.001**
FH - W23	FH - W23		0.451	0.017	**<0.001**
SF-36 MH - W19	SF-36 MH - W19		0.416	0.009	**<0.001**
SF-36 MH - W20	SF-36 MH - W20		0.347	0.007	**<0.001**
SF-36 MH - W21	SF-36 MH - W21		0.323	0.007	**<0.001**
SF-36 MH - W22	SF-36 MH - W22		0.315	0.007	**<0.001**
SF-36 MH - W23	SF-36 MH - W23		0.346	0.008	**<0.001**

Appendix C.3

Model fit statistics and parameter estimates for random-intercept cross lagged panel model assessed using binary measures of financial hardship and mental health.

Model fit indices – Binary measures of financial hardship and mental health.

Model	Model χ^2 (scaled)	df	CFI (robust)	TLI (robust)	RMSEA (robust)	90% CI RMSEA	SRMR
Binary FH/MH	91.68	33	0.995	0.994	0.032	0.022 – 0.041	0.014

Standardised parameter estimates for random-intercept cross-lagged panel model (Binary measures of financial hardship and mental health).

		RI-CLPM (Binary FH/MH)			
Outcome	**Predictor**	**Parameter**	**Estimate (β)**	**SE**	**p-value**
Autoregressive Terms					
FH_t	FH_{t-1}	a1	0.095	0.015	**<0.001**
MH_t	MH_{t-1}	a5	0.173	0.015	**<0.001**
Cross-lagged Terms					
FH_t	MH_{t-1}	b1	0.01	0.013	0.440
MH_t	FH_{t-1}	b5	0.062	0.014	**<0.001**
Covariance Terms					
FH – W19	SF-36 MH – W19	e1	-0.045	0.033	<0.182
FH – W20	SF-36 MH – W20	e2	-0.011	0.041	0.794
FH – W21	SF-36 MH – W21	e3	-0.034	0.040	0.403
FH – W22	SF-36 MH – W22	e4	-0.130	0.040	**0.001**
FH – W23	SF-36 MH – W23	e5	-0.132	0.038	**<0.001**
RI – FH	RI – MH		-1.014	0.050	**<0.001**
Variance Terms					
RI – FH	RI – FH		1.675	0.077	**<0.001**
RI – MH	RI – MH		1.910	0.084	**<0.001**

Appendix C.4

Model fit statistics and parameter estimates for random-intercept cross lagged panel model assessed over 2001-2006, 2007-2012, and 2013-2018.

Model fit indices – 2001-2006, 2007-2012, 2013-2018.

Model	Model χ^2 (scaled)	df	CFI (robust)	TLI (robust)	RMSEA (robust)	90% CI RMSEA	SRMR
2001-2006	385.32	65	0.991	0.991	0.031	0.028 – 0.034	0.029
2007-2012	477.54	54	0.987	0.987	0.039	0.036 – 0.042	0.034
2013-2018	397.56	65	0.993	0.993	0.028	0.025 – 0.031	0.032

Standardised parameter estimates for random-intercept cross-lagged panel model – 2001-2006.

		Partially Constrained RI-CLPM - 2001-2006			
Outcome	**Predictor**	**Parameter**	**Estimate**	**SE**	**p-value**
Autoregressive Terms					
FH_t	FH_{t-1}	a1	0.169	0.012	**<0.001**
MH_t	MH_{t-1}	a5	0.141	0.007	**<0.001**
Cross-lagged Terms					
FH_t	MH_{t-1}	b1	-0.015	0.006	**0.021**
MH_t	FH_{t-1}	b5	-0.008	0.006	0.211
Covariance Terms					
FH - W1	SF-36 MH - W1	e1	-0.071	0.008	**<0.001**
FH - W2	SF-36 MH - W2	e2	-0.038	0.006	**<0.001**
FH - W3	SF-36 MH - W3	e3	-0.035	0.006	**<0.001**
FH - W4	SF-36 MH - W4	e4	-0.029	0.006	**<0.001**
FH - W5	SF-36 MH - W5	e5	-0.031	0.006	**<0.001**
FH - W6	SF-36 MH - W6	e6	-0.038	0.007	**<0.001**
RI - FH	RI - MH		-0.171	0.009	**<0.001**
Variance Terms					
RI - FH	RI - FH		0.441	0.018	**<0.001**
RI - MH	RI - MH		0.451	0.011	**<0.001**
FH - W1	FH - W1		0.524	0.018	**<0.001**
FH - W2	FH - W2		0.472	0.020	**<0.001**
FH - W3	FH - W3		0.423	0.018	**<0.001**
FH - W4	FH - W4		0.392	0.017	**<0.001**
FH - W5	FH - W5		0.404	0.016	**<0.001**
FH - W6	FH - W6		0.455	0.020	**<0.001**
SF-36 MH - W1	SF-36 MH - W1		0.528	0.011	**<0.001**
SF-36 MH - W2	SF-36 MH - W2		0.425	0.010	**<0.001**
SF-36 MH - W3	SF-36 MH - W3		0.400	0.009	**<0.001**
SF-36 MH - W4	SF-36 MH - W4		0.396	0.010	**<0.001**
SF-36 MH - W5	SF-36 MH - W5		0.399	0.010	**<0.001**
SF-36 MH - W6	SF-36 MH - W6		0.410	0.010	**<0.001**

* Autoregressive (a1, a5) and cross-lagged (b1, b5) paths were constrained to be equal across adjacent waves (1-6).

Standardised parameter estimates for random-intercept cross-lagged panel model – 2007-2012.

		Partially Constrained RI-CLPM - 2007-2012			
Outcome	**Predictor**	**Parameter**	**Estimate**	**SE**	**p-value**
Autoregressive Terms					
FH_t	FH_{t-1}	a1	0.129	0.013	**<0.001**
MH_t	MH_{t-1}	a5	0.108	0.007	**<0.001**
Cross-lagged Terms					
FH_t	MH_{t-1}	b1	-0.025	0.007	**<0.001**
MH_t	FH_{t-1}	b5	-0.004	0.006	0.519
Covariance Terms					
FH - W7	SF-36 MH - W7	e1	-0.066	0.008	**<0.001**
FH - W8	SF-36 MH - W8	e2	-0.026	0.007	**<0.001**
FH - W9	SF-36 MH - W9	e3	-0.032	0.007	**<0.001**
FH - W11	SF-36 MH - W11	e4	-0.034	0.006	**<0.001**
FH - W12	SF-36 MH - W12	e5	-0.032	0.006	**<0.001**
RI - FH	RI - MH		-0.195	0.010	**<0.001**
Variance Terms					
RI - FH	RI - FH		0.533	0.021	**<0.001**
RI - MH	RI - MH		0.503	0.012	**<0.001**
FH - W7	FH - W7		0.504	0.022	**<0.001**
FH - W8	FH - W8		0.402	0.018	**<0.001**
FH - W9	FH - W9		0.393	0.019	**<0.001**
FH - W11	FH - W11		0.430	0.017	**<0.001**
FH - W12	FH - W12		0.402	0.015	**<0.001**
SF-36 MH - W7	SF-36 MH - W7		0.453	0.011	**<0.001**
SF-36 MH - W8	SF-36 MH - W8		0.379	0.009	**<0.001**
SF-36 MH - W9	SF-36 MH - W9		0.379	0.010	**<0.001**
SF-36 MH - W10	SF-36 MH - W10		0.385	0.009	**<0.001**
SF-36 MH - W11	SF-36 MH - W11		0.386	0.009	**<0.001**
SF-36 MH - W12	SF-36 MH - W12		0.394	0.009	**<0.001**

* Autoregressive (a1, a5) and cross-lagged (b1, b5) paths were constrained to be equal across adjacent waves (7-12).

Standardised parameter estimates for random-intercept cross-lagged panel model – 2013-2018.

		Partially Constrained RI-CLPM - 2013-2018			
Outcome	**Predictor**	**Parameter**	**Estimate**	**SE**	**p-value**
Autoregressive Terms					
FH_t	FH_{t-1}	a1	0.185	0.012	**<0.001**
MH_t	MH_{t-1}	a5	0.117	0.006	**<0.001**
Cross-lagged Terms					
FH_t	MH_{t-1}	b1	0.002	0.006	0.688
MH_t	FH_{t-1}	b5	0.002	0.005	0.673
Covariance Terms					
FH - W13	SF-36 MH - W13	e1	-0.055	0.007	**<0.001**
FH - W14	SF-36 MH - W14	e2	-0.030	0.005	**<0.001**
FH - W15	SF-36 MH - W15	e3	-0.035	0.005	**<0.001**
FH - W16	SF-36 MH - W16	e4	-0.028	0.005	**<0.001**
FH - W17	SF-36 MH - W17	e5	-0.019	0.005	**<0.001**
FH - W18	SF-36 MH - W18	e6	-0.045	0.006	**<0.001**
RI - FH	RI - MH		-0.204	0.009	**<0.001**
Variance Terms					
RI - FH	RI - FH		0.457	0.019	**<0.001**
RI - MH	RI - MH		0.519	0.010	**<0.001**
FH - W13	FH - W13		0.536	0.019	**<0.001**
FH - W14	FH - W14		0.410	0.015	**<0.001**
FH - W15	FH - W15		0.388	0.013	**<0.001**
FH - W16	FH - W16		0.402	0.015	**<0.001**
FH - W17	FH - W17		0.420	0.016	**<0.001**
FH - W18	FH - W18		0.438	0.016	**<0.001**
SF-36 MH - W13	SF-36 MH - W13		0.446	0.009	**<0.001**
SF-36 MH - W14	SF-36 MH - W14		0.368	0.008	**<0.001**
SF-36 MH - W15	SF-36 MH - W15		0.356	0.007	**<0.001**
SF-36 MH - W16	SF-36 MH - W16		0.354	0.007	**<0.001**
SF-36 MH - W17	SF-36 MH - W17		0.364	0.007	**<0.001**
SF-36 MH - W18	SF-36 MH - W18		0.387	0.008	**<0.001**

* Autoregressive (a1, a5) and cross-lagged (b1, b5) paths were constrained to be equal across adjacent waves (13-18).

Appendix C.5

Comparison of respondents across sex, age, financial hardship, and mental health, with respect to whether responded to all waves or not.

	All Waves - Yes		All Waves - No	
Characteristic	**n**	**%**	**n**	**%**
Total	54,170	79.0	14,402	21.0
Sex				
Males	24,360	45.0	7,271	50.5
Females	29,810	55.0	7,131	49.5
Age				
15-19	1,659	3.1	1,002	7.0
20-29	7,334	13.5	3,215	22.3
30-39	9,732	18.0	2,793	19.4
40-49	8,080	14.9	1,978	13.7
50-59	9,234	17.0	1,861	12.9
60-69	9,039	16.7	1,442	10.0
70+	9,092	16.8	2,111	14.7
Financial Hardship				
Yes	9,519	17.6	3,406	23.6
No	44,651	82.4	10,996	76.4
Mental Health (SF-36)				
91-100	7,758	14.3	1,613	11.2
81-90	11,420	21.1	2,511	17.4
71-80	13,974	25.8	3,655	25.4
61-70	6,552	12.1	1,772	12.3
51-60	7,568	14.0	2,341	16.3
41-50	2,976	5.5	1,006	7.0
31-40	2,333	4.3	821	5.7
21-30	775	1.4	270	1.9
11-20	547	1.0	198	1.4
0-10	126	0.2	68	0.5
NA	141	0.3	147	1.0

Appendix D – Supplementary Material for Chapter 5

Appendix D.1

Comparison of baseline (wave 14) sociodemographic characteristics between respondents with complete data across waves 14-23 (All Waves) and respondents without complete data (Part Waves).

	Part Waves		All Waves	
Characteristic	**n**	**%**	**n**	**%**
Sex				
Male	4,208	49.35	3,098	43.83
Female	4,319	50.65	3,970	56.17
Age Cat				
15-19	848	9.94	374	5.29
20-29	1,826	21.41	1,061	15.01
30-39	1,186	13.91	1,178	16.67
40-49	1,245	14.6	1,294	18.31
50-59	1,151	13.5	1,480	20.94
60-69	942	11.05	1,131	16
70+	1,329	15.59	550	7.78
Birth Cohort				
1900-1929	258	3.03	14	0.2
1930-1949	1,540	18.06	1,050	14.86
1950-1969	2,234	26.2	2,733	38.67
1970-1989	2,649	31.07	2,435	34.45
1990-2009	1,846	21.65	836	11.83
SEIFA				
5	1,642	19.26	1,457	20.61
4	1,715	20.11	1,515	21.43
3	1,718	20.15	1,432	20.26
2	1,638	19.21	1,372	19.41
1	1,811	21.24	1,291	18.27
NA	3	0.04	1	0.01
Education				
Postgrad	352	4.13	454	6.42
Undergrad	1,400	16.42	1,729	24.46
Diploma/Vocational	2,661	31.21	2,281	32.27
Year 12	1,331	15.61	1,028	14.54
Year 11 or below	2,776	32.56	1,574	22.27
Undetermined	7	0.08	2	0.03
Employment				
Full Time	3,237	37.96	3,077	43.53
Part Time	1,754	20.57	1,702	24.08
Unemployed	408	4.78	226	3.2
Not in labour force	3,128	36.68	2,063	29.19
Income Quintile (Household)				
5	1,812	21.25	1,982	28.04
4	1,814	21.27	1,661	23.5
3	1,730	20.29	1,471	20.81
2	1,822	21.37	1,260	17.83
1	1,349	15.82	694	9.82
Physical Functioning (SF-36)				
91-100	4,329	50.77	3,993	56.49
81-90	1,168	13.7	1,268	17.94

71-80	634	7.44	569	8.05
61-70	450	5.28	346	4.9
51-60	373	4.37	225	3.18
41-50	417	4.89	251	3.55
31-40	278	3.26	142	2.01
21-30	299	3.51	113	1.6
11-20	223	2.62	83	1.17
0-10	276	3.24	60	0.85
NA	80	0.94	18	0.25
Mental Health (SF-36)				
91-100	1,329	15.59	1,266	17.91
81-90	1,854	21.74	1,734	24.53
71-80	2,152	25.24	1,903	26.92
61-70	983	11.53	765	10.82
51-60	1,129	13.24	762	10.78
41-50	420	4.93	278	3.93
31-40	361	4.23	230	3.25
21-30	120	1.41	68	0.96
11-20	103	1.21	44	0.62
0-10	30	0.35	18	0.25
NA	46	0.54	NA	NA
Financial Hardship (Yes/No)				
0	5,984	70.18	5,738	81.18
1	2,042	23.95	1,330	18.82
NA	501	5.88	NA	NA
Financial Hardship (0-7)				
0	5,984	70.18	5,738	81.18
1	883	10.36	632	8.94
2	492	5.77	314	4.44
3	311	3.65	192	2.72
4	165	1.94	105	1.49
5	99	1.16	51	0.72
6	58	0.68	22	0.31
7	34	0.4	14	0.2
NA	501	5.88	NA	NA

Appendix D.2

State distribution tables detailing the proportion of respondents in each state over time and associated entropy. Proportions are derived using an ‘expert’ approach to optimal matching and k = 2 clusters.

Cluster 1 – State distribution

State	Wave 14	Wave 15	Wave 16	Wave 17	Wave 18	Wave 19	Wave 20	Wave 21	Wave 22	Wave 23
N	0.850	0.863	0.878	0.878	0.878	0.878	0.888	0.895	0.904	0.873
C	0.098	0.089	0.083	0.085	0.080	0.076	0.071	0.071	0.064	0.075
D	0.020	0.019	0.014	0.016	0.017	0.021	0.022	0.017	0.016	0.021
B	0.032	0.029	0.025	0.021	0.025	0.025	0.020	0.017	0.016	0.030

Cluster 2 – State distribution

State	Wave 14	Wave 15	Wave 16	Wave 17	Wave 18	Wave 19	Wave 20	Wave 21	Wave 22	Wave 23
N	0.198	0.180	0.140	0.130	0.066	0.088	0.140	0.170	0.160	0.170
C	0.205	0.140	0.130	0.160	0.139	0.137	0.120	0.140	0.170	0.130
D	0.095	0.110	0.130	0.130	0.152	0.152	0.170	0.140	0.180	0.180
B	0.501	0.560	0.600	0.570	0.643	0.623	0.560	0.540	0.480	0.520

Entropy scores for each cluster over time

Cluster	Wave 14	Wave 15	Wave 16	Wave 17	Wave 18	Wave 19	Wave 20	Wave 21	Wave 22	Wave 23
1	0.400	0.380	0.340	0.340	0.340	0.350	0.330	0.310	0.290	0.360
2	0.880	0.830	0.800	0.830	0.740	0.770	0.840	0.860	0.910	0.880

Appendix D.3

Model summary – time heterogeneous model ($k = 4$).

Item-response probabilities

	State			
Item	**1**	**2**	**3**	**4**
Cashflow Probs.	2.0%	13.2%	54.5%	96.5%
Deprivation	0.6%	41.7%	6.8%	85.1%

Latent state membership probabilities

State	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
1	0.749	0.766	0.769	0.768	0.773	0.772	0.789	0.802	0.808	0.786
2	0.042	0.042	0.046	0.047	0.052	0.055	0.064	0.050	0.056	0.053
3	0.147	0.130	0.127	0.132	0.116	0.114	0.100	0.102	0.094	0.099
4	0.063	0.062	0.058	0.053	0.060	0.059	0.048	0.047	0.042	0.063

Transition probability matrices between each time point

Time	2
Wave	15

	To State (t+1)			
From State (t)	**1**	**2**	**3**	**4**
1	0.998	0.002	0.000	0.000
2	0.075	0.859	0.000	0.066
3	0.094	0.000	0.837	0.070
4	0.032	0.078	0.111	0.780

Time	3
Wave	16

	To State (t+1)			
From State (t)	**1**	**2**	**3**	**4**
1	0.984	0.005	0.005	0.006
2	0.110	0.844	0.000	0.046
3	0.064	0.000	0.886	0.049
4	0.036	0.105	0.133	0.727

Time	4
Wave	17

	To State (t+1)			
From State (t)	**1**	**2**	**3**	**4**
1	0.978	0.004	0.016	0.001
2	0.074	0.802	0.000	0.125
3	0.093	0.000	0.862	0.045
4	0.015	0.125	0.167	0.694

Time	5
Wave	18

	To State (t+1)			
From State (t)	**1**	**2**	**3**	**4**
1	0.983	0.010	0.007	0.000
2	0.070	0.817	0.000	0.113
3	0.100	0.000	0.814	0.086
4	0.022	0.097	0.066	0.815

Time	6
Wave	19

	To State (t+1)			
From State (t)	**1**	**2**	**3**	**4**
1	0.984	0.003	0.010	0.003
2	0.000	0.909	0.000	0.091
3	0.100	0.000	0.837	0.063
4	0.000	0.104	0.150	0.746

Time	7
Wave	20

	To State (t+1)			
From State (t)	**1**	**2**	**3**	**4**
1	0.976	0.006	0.017	0.001
2	0.137	0.849	0.000	0.014
3	0.240	0.004	0.695	0.061
4	0.000	0.207	0.125	0.669

Time	8
Wave	21

	To State (t+1)			
From State (t)	**1**	**2**	**3**	**4**
1	0.985	0.000	0.014	0.000
2	0.173	0.724	0.000	0.103
3	0.109	0.000	0.842	0.050
4	0.051	0.065	0.138	0.746

Time	9
Wave	22

	To State (t+1)			
From State (t)	**1**	**2**	**3**	**4**
1	0.991	0.005	0.004	0.001
2	0.026	0.923	0.000	0.052
3	0.114	0.000	0.847	0.040
4	0.027	0.136	0.103	0.735

Time	10
Wave	23

	To State (t+1)			
From State (t)	**1**	**2**	**3**	**4**
1	0.967	0.008	0.020	0.006
2	0.000	0.818	0.000	0.182
3	0.000	0.000	0.882	0.118
4	0.106	0.026	0.000	0.869

Appendix D.4

Model summary – time homogeneous model (k = 8).

Item-response probabilities

	State							
Item	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Cashflow Probs.	0.8%	2.3%	19.5%	76.9%	0.1%	85.8%	16.0%	95.5%
Deprivation	0.0%	11.6%	0.0%	55.8%	0.0%	10.8%	75.0%	86.5%

Latent state membership probabilities

State	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
1	0.632	0.625	0.621	0.617	0.615	0.614	0.613	0.613	0.613	0.613
2	0.075	0.076	0.078	0.079	0.081	0.083	0.084	0.085	0.087	0.088
3	0.092	0.109	0.121	0.130	0.136	0.141	0.144	0.147	0.149	0.150
4	0.032	0.033	0.034	0.035	0.036	0.036	0.037	0.037	0.037	0.037
5	0.033	0.033	0.033	0.033	0.033	0.032	0.032	0.032	0.032	0.031
6	0.079	0.065	0.055	0.047	0.042	0.037	0.034	0.031	0.029	0.027
7	0.012	0.013	0.014	0.015	0.016	0.017	0.017	0.018	0.018	0.018
8	0.047	0.046	0.044	0.043	0.042	0.040	0.039	0.037	0.036	0.035

Transition probability matrix

	To State (t+1)							
From State (t)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	0.963	0.013	0.022	0.002	0.000	0.000	0.000	0.000
2	0.072	0.847	0.052	0.021	0.000	0.000	0.008	0.000
3	0.083	0.012	0.856	0.047	0.000	0.003	0.000	0.000
4	0.120	0.082	0.011	0.487	0.299	0.000	0.000	0.000
5	0.000	0.000	0.000	0.288	0.504	0.107	0.024	0.077
6	0.000	0.000	0.148	0.014	0.051	0.750	0.000	0.037
7	0.000	0.071	0.000	0.000	0.025	0.000	0.870	0.034
8	0.000	0.000	0.000	0.000	0.064	0.049	0.032	0.855

Appendix D.5

Person-years in each latent state by key demographic factors, pooled across all ten annual waves of analysis – row proportions.

Characteristic	Total (n)	1 (n)	2 (n)	3 (n)	4 (n)	1 (%)	2 (%)	3 (%)	4 (%)
Sex									
Male	30,990	25,586	2,782	1,354	1,268	*82.6*	*9.0*	*4.4*	*4.1*
Female	39,690	30,838	4,625	1,762	2,465	*77.7*	*11.7*	*4.4*	*6.2*
Age Category									
15-19	1,120	937	98	50	35	*83.7*	*8.8*	*4.5*	*3.1*
20-29	7,988	5,552	1,415	342	679	*69.5*	*17.7*	*4.3*	*8.5*
30-39	11,827	8,545	1,723	553	1,006	*72.2*	*14.6*	*4.7*	*8.5*
40-49	12,351	9,255	1,687	557	852	*74.9*	*13.7*	*4.5*	*6.9*
50-59	14,304	11,506	1,441	681	676	*80.4*	*10.1*	*4.8*	*4.7*
60-69	12,822	11,208	661	592	361	*87.4*	*5.2*	*4.6*	*2.8*
70+	10,268	9,421	382	341	124	*91.8*	*3.7*	*3.3*	*1.2*
Birth Cohort									
1990-2009	8,358	5,999	1,312	400	647	*71.8*	*15.7*	*4.8*	*7.7*
1970-1989	24,334	17,898	3,495	1,088	1,853	*73.6*	*14.4*	*4.5*	*7.6*
1950-1969	27,344	22,722	2,212	1,300	1,110	*83.1*	*8.1*	*4.8*	*4.1*
1930-1949	10,506	9,689	384	315	118	*92.2*	*3.7*	*3.0*	*1.1*
1900-1929	138	116	4	13	5	*84.1*	*2.9*	*9.4*	*3.6*
SEIFA									
5 (Greatest Advantage)	14,141	12,447	1,046	364	284	*88.0*	*7.4*	*2.6*	*2.0*
4	14,969	12,463	1,420	517	569	*83.3*	*9.5*	*3.5*	*3.8*
3	14,484	11,624	1,609	581	670	*80.3*	*11.1*	*4.0*	*4.6*
2	14,000	10,813	1,609	693	885	*77.2*	*11.5*	*5.0*	*6.3*
1	13,037	9,046	1,718	955	1,318	*69.4*	*13.2*	*7.3*	*10.1*
NA	49	31	5	6	7	*63.3*	*10.2*	*12.2*	*14.3*
Education									
Postgrad	5,601	5,049	364	100	88	*90.1*	*6.5*	*1.8*	*1.6*
Undergrad	18,359	15,678	1,540	646	495	*85.4*	*8.4*	*3.5*	*2.7*
Diploma/Vocational	23,924	18,103	2,875	1,289	1,657	*75.7*	*12.0*	*5.4*	*6.9*
Year 12	9,350	7,027	1,258	387	678	*75.2*	*13.5*	*4.1*	*7.3*
Year 11 or below	13,426	10,547	1,370	694	815	*78.6*	*10.2*	*5.2*	*6.1*
Undetermined	20	20	NA	NA	NA	*100.0*	*NA*	*NA*	*NA*
Employment									
Full Time	30,436	24,968	3,490	955	1,023	*82.0*	*11.5*	*3.1*	*3.4*
Part Time	15,539	12,057	1,937	634	911	*77.6*	*12.5*	*4.1*	*5.9*
Unemployed	1,607	853	252	185	317	*53.1*	*15.7*	*11.5*	*19.7*
Not in labour force	23,098	18,546	1,728	1,342	1,482	*80.3*	*7.5*	*5.8*	*6.4*
Income Quintile (Household)									
5 (Highest)	19,585	17,990	1,044	316	235	*91.9*	*5.3*	*1.6*	*1.2*
4	17,121	14,297	1,847	522	455	*83.5*	*10.8*	*3.0*	*2.7*
3	14,067	10,555	2,032	622	858	*75.0*	*14.4*	*4.4*	*6.1*
2	12,447	8,626	1,639	932	1,250	*69.3*	*13.2*	*7.5*	*10.0*
1	7,460	4,956	845	724	935	*66.4*	*11.3*	*9.7*	*12.5*
Physical Functioning (SF-36)									
91-100	36,468	30,114	3,830	1,123	1,401	*82.6*	*10.5*	*3.1*	*3.8*
81-90	12,833	10,505	1,233	516	579	*81.9*	*9.6*	*4.0*	*4.5*
71-80	6,474	5,177	636	289	372	*80.0*	*9.8*	*4.5*	*5.7*
61-70	4,083	3,099	450	246	288	*75.9*	*11.0*	*6.0*	*7.1*
51-60	2,813	2,073	310	191	239	*73.7*	*11.0*	*6.8*	*8.5*
41-50	2,438	1,652	304	222	260	*67.8*	*12.5*	*9.1*	*10.7*
31-40	1,687	1,150	190	169	178	*68.2*	*11.3*	*10.0*	*10.6*
21-30	1,396	915	155	136	190	*65.5*	*11.1*	*9.7*	*13.6*
11-20	1,010	673	132	103	102	*66.6*	*13.1*	*10.2*	*10.1*
0-10	900	600	110	92	98	*66.7*	*12.2*	*10.2*	*10.9*
NA	578	466	57	29	26	*80.6*	*9.9*	*5.0*	*4.5*
Mental Health (SF-36)									
91-100	11,718	10,722	643	213	140	*91.5*	*5.5*	*1.8*	*1.2*
81-90	16,518	14,487	1,267	410	354	*87.7*	*7.7*	*2.5*	*2.1*
71-80	18,691	15,307	1,943	728	713	*81.9*	*10.4*	*3.9*	*3.8*
61-70	7,974	6,001	1,030	435	508	*75.3*	*12.9*	*5.5*	*6.4*
51-60	8,583	5,907	1,301	607	768	*68.8*	*15.2*	*7.1*	*8.9*
41-50	3,173	1,959	509	265	440	*61.7*	*16.0*	*8.4*	*13.9*
31-40	2,502	1,419	414	257	412	*56.7*	*16.5*	*10.3*	*16.5*
21-30	806	382	166	83	175	*47.4*	*20.6*	*10.3*	*21.7*
11-20	561	194	111	89	167	*34.6*	*19.8*	*15.9*	*29.8*
0-10	154	46	23	29	56	*29.9*	*14.9*	*18.8*	*36.4*