

The Dynamics of Household Financial Hardship: Entry, Duration, Persistence and Recurrence

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Abstract

We study the dynamics of household financial hardship by distinguishing its different forms and accommodating the complexity in trajectory and recurrence. Based on the annual Household, Income and Labour Dynamics in Australia (HILDA) Survey data from 2001 to 2022, we use a multi-level competing risks survival framework to study the entry, spell duration, persistence and recurrence of hardship. Our results show that: (i) inability to pay utility bills is the primary gateway into hardship, accounting for nearly half of the first episodes; ii) spells begin with asking welfare support take longer to recover from than those start in less severe forms; (iii) burdens of rent and mortgage are dominant risk factors, while education, income and marriage mitigate risk; (iv) the risk of households currently in hardship to stay in hardship next year is 160% higher than those not current in hardship, highlighting persistence in hardship experience; (v) households entrenched in recurrent hardship exhibit substantially elevated risk of falling into repeat spells much sooner than households with less or no prior experience. These results highlight the need for policy measures that support early identification and intervention, alongside efforts to address the structural drivers of hardship, including housing affordability, education access, and job security.

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1. Introduction

Households experience financial hardship when they do not have sufficient monetary resource to pay for life essentials and financial obligations, such as food, housing, utilities, and medical care. Unlike poverty which is measured by income level, or financial fragility which is measured by availability or adequacy of financial resources, financial hardship captures the lived experience of material deprivation which reflects realised financial distress (Mayer and Jencks, 1989). As such, hardship has more immediate and direct implications for wellbeing, physical and mental health, and long-term economic security (Butterworth et al., 2009, 2012; Marshall and Tucker-Seeley, 2018; Turunen & Hiilamo, 2014).

Against a backdrop of rising living costs, greater income volatility, and increased reliance on household debt, hardship has become increasingly prevalent worldwide over recent decades (Thomas, 2022; Pilkauskas, 2012; Bourova et al., 2019). Despite its growing importance, much of the existing literature on hardship is dated, highlighting the need for new research to provide more contemporary evidence and new insights into the dynamics of hardship. Furthermore, most existing research on financial hardship treat hardship as a static state at a point of time or within a defined timeframe, identifying hardship by a single indicator, and focusing on providing descriptive statistics or estimating the probability of hardship.

As hardship experience can take different forms, span over multiple periods, and reoccur after exit, new studies need to place more emphasis on the dynamic aspects of hardship experiences rather than treating hardship as a single and homogeneous experience. The poverty dynamics literature provides a useful framework for such an approach, showing evidence that recurrent poverty is common, and spell duration influences both exit and re-entry probabilities (Bane & Ellwood, 1986; Cantó, 2002). Furthermore, previous exposure to poverty has also been shown to increase the likelihood of future poverty through mechanisms such as resource depletion, labour-market detachment, and psychological scarring (Heckman, 1981; Stevens, 1999). However, these ideas have rarely been applied to studying dynamics of hardship, despite clear conceptual parallels of hardship and poverty. Except for Brown et al. (2014), which offer some evidence of persistence in hardship, existing literature offers little insight into the dynamic processes through which hardship emerges, develops and accumulate over time.

We argue that different forms of hardship may play distinct roles within a household's hardship trajectory. For example, difficulty paying bills or reliance on assistance from family and friends may represent relatively early and potentially reversible forms of financial stress, whereas food insecurity or housing instability may signal deeper and more entrenched

deprivation. Treating hardship indicators as interchangeable risks obscuring important processes of sequencing, escalation, and recovery (Berthoud & Bryan, 2011). Understanding how hardship begins, accumulates, and resolves therefore requires an explicitly dynamic approach. In this study, we view financial hardship as a process that can take different forms and have different structures. We explore the complexity and temporal dimensions of hardship trajectories and acknowledge that different forms of hardship may play distinct roles within a household's hardship trajectory. The sample and data of this study come from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which provides the annual data covering 43,784 unique households over the period 2001 to 2022. We study the Australian household data for two reasons. First, the growth of living costs and household debt in Australia is one of the fastest in the world: household living costs increased by 94% between 2000 and 2024 in Australia, while growing numbers of households have sought hardship grants to pay for basic utilities such as electricity (ABS, 2026). In our sample, approximately one in five households experienced hardship at least once. Furthermore, in a dataset recently published by the International Monetary Fund (IMF, 2025), Australia has become the second most indebted country since 2016, with household debts increased sharply from 88% of GDP in 2000 to 112% in 2024.

Secondly, the HILDA survey data has several features that make it particularly suitable for analysing hardship dynamics. Survey waves have been conducted annually, while consistent measures of hardship are used across survey waves. The annual frequency of this dataset allows us to make close observation of transitions into and out of hardship, facilitating the longitudinal analysis of entry, recurrence, duration, and recurrence. In addition, the surveys have consistently re-interview rates within a range of 87 to 97 percent between consecutive waves, which help minimise attrition bias, a common concern in long-running panel studies (Wooden et al., 2024).

Based on this rich dataset, we study hardship as a dynamic process and analyse the landing, spell duration, persistence, and recurrence of hardship experiences, as well as the effects of various household characteristics. We distinguish seven different forms of hardship and use a semi-parametric survival analysis to model hardship risk and identify the effects of various household characteristics (i.e., covariates). Specifically, we examine which form of hardship emerges first (i.e., landing), why some households recover quickly while others got trapped longer (i.e., spell duration), whether current hardship affects the risk of hardship the next period (i.e., persistence), and how are the risk profiles change for repeat entries of hardship spells (i.e., recurrence).

The results show that difficulty in bill payment is most common form of hardship on landing, accounting for 49.6% of the first episodes. Spell durations vary depending on the severity of first episode: spells starting with bill payment arrears are more transitory than those in more severe forms such as asking for welfare help. Rent and mortgage arrears are dominant risk factors: the risk of rent arrears among public housing households is more than doubled comparing to those in mortgage-free private homes. Education is the most important protective factor, e.g., completing a bachelor's degree reduces the risk of entering hardship by approximately 20 percent. The current hardship experience increases the risk of hardship next year by 160% compared with those not having hardship. Furthermore, households with prior hardship spells tend to enter repeat spells sooner than households with less or no prior hardship experience.

These findings contribute to multiple literatures. For household finance, we move beyond the literature's focus on portfolio choice and asset allocation to characterize the dynamics of financial distress—the opposite pole of household financial outcomes. For poverty research, we adapt competing risks methods developed for income poverty to the distinct concept of material hardship, demonstrating that different hardship types exhibit meaningfully different dynamics. For policy analysis, we identify difficulty in bill payment as an early warning signal, suggesting that a dynamic targeted policy framework would be most effective. Since bill payment difficulty provides an early warning signal, early response assistance programs may prevent hardship compounds into more severe forms, while policies targeting households trapped in prolonged hardships should emphasize housing, education, gender, and job security support.

The remainder of this paper proceeds as follows. Section 2 reviews relevant literature and identifies the specific gaps our analysis addresses. Section 3 provides data descriptions, sample construction, and variable definitions. Section 4 presents our methodological framework. Section 5 reports empirical results. Section 6 concludes.

2. Literature

In this section, we discuss the related literature in three connected areas: financial hardship studies, dynamic perspectives on financial risk persistence and recurrence, and applications of survival and competing risks models in the household financial risk studies.

Financial hardship studies concern about households' ability to meet basic financial obligations in contexts of rising living costs, labour market volatility, and limited financial buffers. Unlike income poverty, which captures resource availability at a point in time,

financial hardship reflects realised financial stress, situations in which households are unable to pay essential expenses, rely on informal support, or reduce consumption below socially acceptable standards (Berthoud & Kempson, 1992; Saunders & Adelman, 2004). Butterworth et al. (2012) find that financial hardship is a more influential factor on the depression experience of Australians than other measures of socio-economic disadvantage such as income poverty and unemployment.

Thomas (2022) reports that more than 40% of American families with children experienced material hardship over a 12-month period. Empirical studies consistently show that financial hardship is associated with substantial welfare losses. Households experiencing hardship report poorer mental and physical health, elevated stress, and lower overall wellbeing, even after controlling for income and employment status (Butterworth et al., 2009; Turunen & Hiilamo, 2014). Bourova et al. (2019) study the surveys of Australians who had trouble paying debt on time and identify unexpected expenses, reliance on Centrelink (social security) income, health problems, unemployment and underemployment as important causes of hardship. They report that financial hardship has adverse impacts on paying for basics, staying healthy, and maintaining socially connected with family, friends and communities. These findings suggest that hardship is not merely an instantaneous inconvenience, but a meaningful indicator of economic vulnerability with potentially lasting adverse consequences.

While this literature establishes the important health, social and welfare implications of financial hardship, much of it treats hardship as a static condition, typically measured as whether a household reports any hardship within a given period. Such approaches provide limited insight into how hardship emerges, whether early difficulties escalate into more severe forms, or how households recover once hardship occurs. Therefore, developing a better understanding financial hardship requires a dynamic perspective.

On the other hand, the poverty dynamics literature demonstrates that economic disadvantage is often characterised by spells of entry, persistence, and exit rather than permanent states (Bane & Ellwood, 1986). A key insight from this literature is that persistence may arise either because past disadvantage causally increases future risk, referred to as true state dependence, or because individuals differ in unobserved characteristics that make them persistently vulnerable, known as spurious state dependence (Heckman, 1981). Although financial hardship may also exhibit persistence and recurrence, the dynamic process concepts studied in the poverty literature has rarely been applied to the studies of financial hardship. A notable exception is Brown et al. (2014), which examined British household survey data to

show that multiple forms of hardship exhibit considerable persistence and are strongly interrelated across successive time periods.

We argue that financial hardship should be studied as a dynamic process as experiencing hardship can be detrimental to the welfare of affected households which may in turn generate negative feedback on the recurrence of hardship in the future. For example, missed bill payments may reduce the households' credit scores, arrears of payments for housing may increase the risk of eviction, and repeated reliance on informal support may erode social capital. These processes suggest that experiencing hardship itself may increase the risk of more future hardships, making recurrence more likely even if other observable characteristics remain unchanged.

Existing empirical work provides indirect support for this view. Studies show that households reporting hardship in one period are significantly more likely to report hardship again in subsequent periods, even after controlling for income and employment transitions (Breunig & Cobb-Clark, 2005; Berthoud & Bryan, 2011). However, most analyses do not explicitly model entry, recurrence, and exit as distinct processes, nor do they distinguish between different forms of hardship. As a result, it remains unclear whether certain hardship experiences function as early warning signals, whether risks intensify with repeated exposure, and how recovery prospects evolve over time.

Survival analysis, originally developed for analysing time-to-event outcomes, provides a natural methodological framework for studying hardship dynamics. Models for analysing survival duration have wide applications in economics literature on topics like unemployment, job tenure, and poverty (Kiefer, 1988; Stevens, 1999). The Cox proportional hazards model, for example, is attractive due to its semi-parametric flexibility, and its ability to estimate the rate at which an event occurs over time while allowing the underlying baseline hazard to remain unspecified. In the context of financial hardship, survival analysis can be used to model the time-point estimate of risk households in hardship, what factors affect the risk outcome, and how fast the survival curve decays. In contrast, static binary models such as logit or probit models can only be used to estimate the probability, but not the speed or timing of risk occurrence. These models cannot be used to identify the survival curve.

An important feature of financial hardship data is that while hardship may take different forms, such as bill payment difficulties, housing stress, or reliance on external assistance, these forms are mutually exclusive as the entry form for each hardship spell. In other words, when analysing hardship spells at the onset, the occurrence of one hardship form precludes observing other forms as the hardship landing event. This structure gives rise to a competing risk setting,

in which multiple potential hardship events compete to occur first. The competing risks models allow hazard rates to vary across hardship types, avoiding the conflation of fundamentally different manifestations of financial distress (Stevens, 1999). This approach is particularly useful for identifying the form of hardship that households experience first for landing analysis in search for the early red flags indicative of subsequent escalation.

It is worth noting that financial hardship can take different forms, such as bill payment difficulties, food insecurity, or reliance on welfare assistance capture different forms of economic strain and may reflect distinct underlying mechanisms. Prior research shows that hardship indicators tend to cluster but do not move uniformly, indicating meaningful heterogeneity in households' experiences of deprivation (Berthoud & Bryan, 2011; Nolan & Whelan, 2011). Despite this, most studies either aggregate hardship indicators into a single index or analyse them independently, without considering their sequencing. Little is known about which forms of hardship households typically encounter first, whether some types are more likely to precede others, or how initial hardship experiences shape subsequent trajectories. Addressing these questions is critical for identifying early intervention points and for understanding how hardship escalates or stabilises over time.

Furthermore, households may enter and exit hardship state multiple times, therefore experience multiple hardship spells. Analysing recurrent events within a survival framework enables the examination of whether risk profiles change with prior hardship experience. Systematic differences in hazard rates across entry spells provide evidence consistent with state dependence, while also allowing for unobserved heterogeneity through clustered standard errors.

This study extends the literature by explicitly recognising that hardship experience can be a dynamic process. Using the longitudinal HILDA data spanning over two decades, we analyse the entry form (landing), spell duration, persistence, and repeat spells of hardship experiences of Australian households. We provide evidence on heterogeneity across various forms of hardship, and how the current hardship affects the risk of repeat hardship spells in future. In doing so, this study contributes to the hardship dynamics literature, and offers a framework for identifying early warning signals and developing effective policies targeted at addressing the most important structural issues.

3. Data

This study uses data from the nationally representative Household, Income and Labour Dynamics in Australia (HILDA) Survey administered by the Melbourne Institute of Applied

Economic and Social Research and funded by the Australian Government Department of Social Services. Started in 2001, the HILDA Survey collects rich information on household composition, income, labour market activity, health, and subjective wellbeing, making it particularly well suited for analysing financial hardship dynamics over time. We draw samples from 22 survey waves from 2001 to 2022, requiring each household to be surveyed in at least two consecutive survey waves to allow the transition from landing to exit being identified. Households enter the hardship risk set when they are first observed in a non-hardship state and contribute observations until hardship entry or censoring. To avoid duplication of household outcomes, the analysis focuses on the household reference person, defined in HILDA as the individual most knowledgeable about the household's finances or the main income earner. This approach is standard in household-level analyses and ensures that each household contributes at most one observation per year (Breunig & Cobb-Clark, 2005; Butterworth et al., 2009). The final sample is an unbalanced longitudinal panel of annual data with 43,784 unique households and 178,000 household-year observations, with 70,679 observations of hardship observations.

The question related to financial hardship in the HILDA survey questionnaire is: *“Since January [last year], did any of the following happen to you because of a shortage of money?”* Participating households are required to self-report whether each of the following events occurred in the previous year:

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

The wording of these items explicitly attributes the behaviour to a shortage of financial resource, ensuring that the indicators capture financial constraint rather than voluntary consumption choices or preferences (Beverly, 2001; Saunders & Adelman, 2004). To avoid duplication of household observations, hardship experience is observed at the household level identified using household reference person - the individual most knowledgeable about the household's finances or the main income earner in HILDA surveys. Hardship spells are defined within a time-to-event of hardship framework. A hardship spell begins when a household previously in a non-hardship state first reported hardship. In survival analysis, observations

that have no hardship occurred during the examination period are right-censored and used for analysis over the remaining periods.

For each form of hardship, we use a binary variable to record households' experience where the households having experienced the hardship during the survey period are assigned a value of one while other households are assigned a value of zero. In addition, we constructed an aggregative measure for landing analysis using a binary variable termed *Any Hardship*, which takes the value of one for households having experienced one or more forms of hardship during the survey period and the value of zero otherwise. Comparing to the alternative aggregate measure that sums up the values of the seven original binary variable values, the binary definition of the aggregate measure is appropriate for conducting survival analysis of hardship entry and recurrence, where the focus is on the timing of first occurrence rather than intensity.

In landing analysis, we treat the seven hardship forms as mutually exclusive competing landing events which occur at the entry point of inflow to a hardship spell. Each hardship form is then analysed separately in cause-specific survival models. For example, a household who's first reported hardship is inability to pay utility bills is identified as landing on a hardship spell with "*Bills Unpaid*" event, while entering a spell in any other forms are treated as no event (right censored) at that time. For a household entering hardship experiencing multiple forms of hardship simultaneously, we create separate spells for each form of landing event for this household. For households that have previously entered and exited a spell, then re-entered a new spell later, we create a discrete variable *Entry#* to denote the sequence of each spell. That is, the initial entry-and-exist spell is recorded as an "Entry1" spell while the next entry to a new spell by the same household is recorded as an "Entry2" spell. Repeat spells with two or more prior spells are combined to form the "Entry3+" sample to avoid the small sample problem for high orders of spells. This way, our dataset accommodates multiple spells for landing analysis and multiple entries for recurrence analysis, while distinguishing seven different forms of hardship for landing and exit analysis.

Table 1 presents the distribution of hardship observations across various *Entry* numbers. Across the 70,679 hardship events, majority of the hardships occurred in a single episode (61.95%), with recurrent spells accounting for less than 40% of the hardships. Nevertheless, less than 10% of the hardship observations are for four or more episodes while less than 1 percent are for households deeply trapped in deprivation with 6 or more entries to hardship spells. Following the synthesis of literature in O'Connor et al. (2019), which document the central role of demographic characteristics, socioeconomic resources, housing

conditions, health, and family circumstances in shaping hardship risk, we collect data for a set of household characteristic variables commonly used in literature as right-hand-side variables (covariates) in risk analysis. The household characteristics we consider include demographic factors (age, sex, and marital status), socioeconomic resources (employment, income, family size, and educational attainment), health, housing tenure and significant life events. Household income is measured as the logarithm of real equivalised household income to reduce skewness and facilitate interpretation. Housing tenure is classified into outright ownership, ownership with a mortgage, private rental, and public or social housing.

Table 1 Distribution of hardships by entry number

	Event count	As percent of total hardships
Entry1	43,784	61.95%
Entry2	15,330	21.69%
Entry3	7,046	9.97%
Entry4	3,049	4.31%
Entry5	1,101	1.56%
Entry6	294	0.42%
Entry7	62	0.09%
Entry8	11	0.02%
Entry9	1	0.00%
Entry10	1	0.00%
No. of hardship observations	70,679	100%

Table 2 presents the summary statistics for our sample. The statistics show that around one-fifth of household-year observations report at least one form of hardship. Furthermore, hardship is most often first expressed through difficulty paying bills which affects 12.1 per cent of observations. On the other hand, more severe forms of hardship, such as going without food, being unable to adequately heat the home, or relying on welfare or community assistance, are reported in fewer than 4 per cent of household-years.

There is also evidence of diverse demographic and socioeconomic characteristics of the households, including substantial variations in family size, household income, educational attainment, housing tenure, and health and adverse life events. Gender representations are roughly equal, and adverse life events are relatively common, posing negative shocks that may trigger entry into financial hardship or contribute to its persistence over time. The combination of repeated observations, heterogeneous economic conditions, and exposure to adverse life events underscores the importance of modelling hardship as a process that unfolds over time rather than as a static outcome.

Table 2 Summary statistics

Variable	N	Mean	SD	Min	Median	Max
Risk/event factors						
Any Hardship	178,331	0.204	0.403	0	0	1
Bills Unpaid	178,331	0.121	0.326	0	0	1
Rent/Mortgage Unpaid	178,331	0.059	0.236	0	0	1
Asked Help	178,331	0.115	0.319	0	0	1
Went Without Food	178,331	0.039	0.194	0	0	1
Unable to Heat Home	178,331	0.032	0.175	0	0	1
Sold/Pawned Possessions	178,331	0.049	0.216	0	0	1
Welfare/Community Help	178,331	0.038	0.192	0	0	1
Demographic characteristics						
Age	178,038	48.896	18.007	15	48	100
Female	178,331	0.505	0.500	0	1	1
Married	174,697	0.440	0.496	0	0	1
Socioeconomic characteristics						
Employed	174,715	0.622	0.485	0	1	1
Log Income	178,331	10.966	0.863	2.398	11.046	14.186
Family Size	178,331	2.443	1.388	1	2	17
Hours Worked	108,603	37.896	14.495	0	40	168
Year 11 or Below (reference)	174,715	0.053	0.223	0	0	1
Year 12	174,715	0.058	0.233	0	0	1
Certificate	174,715	0.143	0.350	0	0	1
Diploma	174,715	0.097	0.296	0	0	1
Graduate Diploma	174,715	0.513	0.500	0	1	1
Bachelor Degree	174,715	0.137	0.343	0	0	1
Postgraduate	174,715	0.000	0.020	0	0	1
Housing tenure factors						
Own Outright (reference)	177,973	0.636	0.481	0	1	1
Own with Mortgage	177,973	0.329	0.470	0	0	1
Renting (Private)	177,973	0.001	0.027	0	0	1
Significant adverse event factors						
Fired/Redundant	178,331	0.195	0.396	0	0	1
Serious Illness	178,331	0.250	0.433	0	0	1
Death in Family	178,331	0.179	0.383	0	0	1
Victim of Violence	178,331	0.182	0.386	0	0	1
Family Member in Jail	178,331	0.170	0.376	0	0	1

Note: Reference indicates a reference category. Negative values in raw HILDA variables are treated as missing data.

4. Methodology

We study hardship dynamics along several interrelated dimensions: landing and spell duration, persistence and recurrence. The landing and duration analysis focused on identifying the forms

of hardship that households often experience when entering a hardship spell and how do exit prospects vary across different landing forms. In persistence analysis, we investigate whether current hardship status affects the risk of hardship occurrence in the following year. In recurrence analysis, we perform comparative analysis to investigate whether hardship spells across different entry numbers have different risk profile, duration or influenced by different household characteristics.

To analyse the timing of hardship occurrence, we employ the Cox proportional hazards model (Cox PH) (Cox, 1972) and its variation, Andersen-Gill model (Andersen and Gill, 1982). These are semi-parametric survival models suitable for analysing the instantaneous risk of experiencing financial hardship (the hazard) without imposing parametric assumptions on the baseline hazard function. Formally, the hazard rate of hardship entry for household i at time t (measured in survey waves), conditional on covariates X_{it} (household characteristics), is specified as:

$$h_i(t|X_i) = h_0(t) \cdot \exp(\beta'X_i) \quad (1)$$

where $h_0(t)$ is the baseline hazard that can be left unspecified, and $\exp(\beta)$ provides estimate of the hazard ratio (HR). $HR > 1$ indicates elevated risk while $HR < 1$ indicates protection. Standard errors are clustered at household level.

The Cox framework is particularly appropriate for analysing hardship risk because it accommodates right-censored observations, allows households to enter and exit the risk set multiple times, and can provide survival time estimates and facilitate comparison of hazard rates across different stages of the hardship process. We apply the model to estimate the risks of hardship in different forms, and for repeat spells in sub-samples of Entry2 and Entry3+.

In *landing* analysis, we estimate cause-specific Cox proportional hazards models within a competing risks framework specified in Equation (2). This approach allows each form of hardship to be analysed individually rather than being assessed only by an aggregate composite outcome measure. The cause-specific hazard of household i entering hardship type j instantaneously at time t , conditional on household characteristics X_{it} , is specified as:

$$h_{ij}(t|X_{it}) = h_{0j}(t) \cdot \exp(X'_{it}\beta_j) \quad (2)$$

where $j \in \{1, \dots, J\}$ denotes the form of first hardship a household experience at the entry to a hardship spell. The seven forms of hardship are treated as competing risks since the occurrence of one form precludes landing on another form of hardship.

Using this model, entry into hardship form j is the only risk event, while entering other hardship forms are treated as no event, or right-censored observation. This cause-specific

framework allows household characteristic effects on hardship risk to vary across different hardship forms, and avoids conflating fundamentally different forms of financial distress, such as payment arrears, material deprivation, and reliance on external assistance (Stevens, 1999).

Since hardship experience may cause damages such as resource depletion or credit impairment (Heckman, 1981), recurrent hardships may have systematic changes in risk profiles across successive entries into hardship spells. Therefore, we examine the repeat hardship spells and compare the risk profiles of initial and repeat entries and compare the effects of household characteristics across different entry levels. Let s denote entry number of a hardship spell, the hazard ratio of household i entering hardship the s -th' time is modelled as:

$$h_i^s(t|X_i t) = h_0^s(t) \cdot \exp(X_i t' \beta^s) \quad (3)$$

where $h_0^s(t)$ is the baseline hazard specific to Entry number s , and β^s is a vector of Entry-specific coefficients.

Model performance is evaluated using Harrell's concordance index (C-index), which measures the model's ability to correctly rank households by their relative risk of hardship entry. The C-index represents the probability that, for a randomly selected pair of households, the household experiencing hardship earlier is assigned a higher predicted risk. In applied survival analysis, C-index values above 0.5 indicates meaningful discriminatory power.

5. Results

This section presents the empirical results, starting with the discussion of landing and spell duration analysis which focuses on the examination of the first form of hardship experienced at the inflow to a hardship spell. Next, we perform persistence analysis to examine whether current hardship experience affects the risk of experiencing hardship in the following year, and compare the risk profiles of recurrent hardship spells.

5.1 Analysis of landing and spell durations

First, we model entry with Any Hardship as an aggregative measure of risk outcome and report the estimation results in Table 3. The coefficients reported represent hazard ratios (HR) converted from the original values estimated using the Cox HR models. A value of $HR > 1$ indicates that a household factor increases hardship risk when the value of corresponding factor increases. A HR at unity indicates a neutral effect of a factor on hardship risk, while $HR < 1$ indicates that a household factor reduces hardship risk when the value of corresponding factor goes up. The C-index values are higher than 0.60, indicating good performance of the four

models and confirming the models' ability to correctly rank observations by households' relative risk of hardship entry.

The results in Table 3 show the most important household factors that increase *Any Hardship* risk are the three housing factors - *Renting (Public Housing)*, *Renting (Private)*, and *Own with Mortgage*, as well as an education tenure - *Certificate*. Hazard ratio estimates for *Renting (Public Housing)* consistently exceeds 2 regardless of model specification, indicating that the risk of rent arrears among public housing households is more than doubled comparing to those in mortgage-free private homes. On the other hand, better education may significantly reduce risk. Comparing to the reference level of *Year 11 or below*, *Postgraduate*, *Graduate Diploma*, and *Bachelor Degree* are the most important risk-reduction factors, consistent with the evidence in literature suggesting that education can improve job security and financial decision-making capacity (Cutler & Lleras-Muney, 2010). These results are consistent across the four models with different specifications.

Referring to Table 3, adverse family events significantly increase the risk of hardship landing, while households headed by Female have 8.3% higher elevated risk (HR = 1.083). Furthermore, Household size is positively associated with risk: each additional household member increases the risk of hardship landing by approximately 5.5%. In contrast, *Married* households has a 16 percent lower risk than the average (HR = 0.840), which is consistent with the role of shared resources and intra-household risk pooling argument. Household income also provides protection against hardship, indicating that a one-unit increase in *Log income* is associated with an approximately 7.5% reduction in hardship landing. This implies that households with double the income face roughly half the risk of experiencing hardship, underscoring income's function as a primary buffer against financial stress (OECD, 2020).

In addition, the hazard ratio of *Age* (0.994) is marginally below unity but nevertheless statistically significant at the one percent level, suggesting protective effect against hardship landing. Although the magnitude of protection is modest at 0.6 percent on a per-year basis, the cumulative effect of age over the life course can be substantial as households gradually build up wealth which provide financial buffer as they grow older. Interesting, while the magnitude of hazard ratios for *Employed* are economically significantly well below unity (HR = 0.774) which suggest economically large risk reduction effects, unfortunately these results are not statistically insignificant at any conventional levels.

Table 3 Cox HR estimates: landing analysis (dependent variable = Any Hardship)

	Model 1	Model 2	Model 3	Model 4
Age	0.994*** (0.001)	0.994*** (0.001)	0.994*** (0.001)	0.994*** (0.001)
Female	1.083*** (0.016)	1.083*** (0.016)	1.083*** (0.016)	1.083*** (0.016)
Married	0.839*** (0.016)	0.840*** (0.016)	0.839*** (0.016)	0.840*** (0.016)
Employed	0.774 (0.262)	0.774 (0.262)	0.774 (0.262)	0.774 (0.262)
Log Income	0.924*** (0.007)	0.925*** (0.007)	0.924*** (0.007)	0.925*** (0.007)
Family Size	1.055*** (0.005)	1.055*** (0.005)	1.055*** (0.005)	1.055*** (0.005)
Hours Worked	0.998*** (0.001)	0.998*** (0.001)	0.998*** (0.001)	0.998*** (0.001)
Postgraduate	0.704*** (0.037)	0.712*** (0.038)	0.704*** (0.037)	0.712*** (0.038)
Graduate Diploma	0.810*** (0.036)	0.816*** (0.036)	0.810*** (0.036)	0.816*** (0.036)
Bachelor Degree	0.788*** (0.022)	0.792*** (0.022)	0.788*** (0.022)	0.792*** (0.022)
Diploma	0.956 (0.027)	0.957 (0.027)	0.956 (0.027)	0.957 (0.027)
Certificate	1.123*** (0.018)	1.122*** (0.018)	1.123*** (0.018)	1.122*** (0.018)
Year 12	0.995 (0.020)	0.996 (0.020)	0.995 (0.020)	0.996 (0.020)
Own with Mortgage	1.399*** (0.016)	1.399*** (0.016)	1.399*** (0.016)	1.399*** (0.016)
Renting (Public Housing)	2.152*** (0.162)	2.120*** (0.161)	2.152*** (0.162)	2.120*** (0.161)
Renting (Private)	1.160*** (0.045)	1.159** (0.045)	1.160*** (0.045)	1.159** (0.045)
Fired/Redundant	1.017 (0.012)	1.017 (0.012)	1.017 (0.012)	1.017 (0.012)
Serious Illness	0.984 (0.016)	0.982 (0.016)	0.984 (0.016)	0.982 (0.016)
Death in Family	1.096*** (0.010)	1.097*** (0.010)	1.096*** (0.010)	1.097*** (0.010)
Victim of Violence	1.042*** (0.012)	1.042*** (0.012)	1.042*** (0.012)	1.042*** (0.012)
Family Member in Jail	1.097*** (0.009)	1.097*** (0.009)	1.097*** (0.009)	1.097*** (0.009)
State FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
No. of observations	32,250	32,250	32,250	32,250
No. of landing events	13,420	13,420	13,420	13,420
Log-likelihood	-128,586.19	-128,568.75	-128,586.19	-128,568.75
Pseudo R ²	0.574	0.574	0.574	0.574
LR Chi ²	1,611.3***	1,646.2***	1,611.3***	1,646.2***
C-index	0.618	0.619	0.618	0.619

To compare the relative contribution of each household characteristic to model discrimination, we present variable importance score estimates in Table 4. The results suggest that housing tenure, employment, education and marital status are the most important explanatory variable. Note that *Age* adds little incremental information for distinguishing hardship risk once other factors are accounted for, reflecting the fact that, within the working-age sample, much of the information in *Age* is mediated through correlated life-course characteristics already captured in the model, such as income, family structure, and housing tenure. This result reinforces the primacy of structural economic conditions, particularly income and housing security in shaping hardship risk, consistent with Harrell (2015).

Table 4 Variable importance scores: landing analysis (dependent variable = Any Hardship)

Covariates	Model 1	Model 2	Model 3	Model 4
Renting (Public Housing)	0.7666	0.7515	0.7666	0.7515
Postgraduate	0.3503	0.3399	0.3503	0.3399
Own with Mortgage	0.3361	0.3360	0.3361	0.3360
Employed	0.2561	0.2557	0.2561	0.2557
Bachelor Degree	0.2377	0.2332	0.2377	0.2332
Graduate Diploma	0.2107	0.2030	0.2107	0.2030
Married	0.1758	0.1747	0.1758	0.1747
Renting (Private)	0.1481	0.1472	0.1481	0.1472
Certificate	0.1160	0.1155	0.1160	0.1155
Family Member in Jail	0.0925	0.0922	0.0925	0.0922
Death in Family	0.0921	0.0924	0.0921	0.0924
Female	0.0799	0.0794	0.0799	0.0794
Log Income	0.0790	0.0775	0.0790	0.0775
Family Size	0.0536	0.0539	0.0536	0.0539
Diploma	0.0449	0.0440	0.0449	0.0440
Age	-	-	-	-
State FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes

Note. Importance scores are reported for household characteristics (covariates), listed in the descending order of the scores in column 2. Each score measures a covariate's contribution to model discrimination for the corresponding hardship-specific Cox model, computed from the full model specification for each hardship type and reflect relative, not causal, importance. Higher values indicate greater contributions.

Next, we turn to the analysis of risk of the seven different forms of hardship that households experience first upon entering a hardship spell. First, we identify what are the common forms of hardships at landing. Having a good understanding of the landing form can provide useful information for developing policies to intervene early when financial strains emerge before households slipping into severe deprivation states over prolonged period. In the second step, we estimate hazard functions to compare the rates at which different forms of hardship events happen over time and examine the effects of various household characteristics on the risk of each form of landing hardship.

In Table 5 and Figure 1, we present the empirical distribution of different forms of hardship observed at the entry of hardship spells. Across the 23,547 landing hardships, *Bills Unpaid* is the most common form, contributing 11,668 observations. The dominant landing form is *Bills Unpaid*, accounting for 49.6% of all first hardship episodes. The second most common form is *Asked Help* (30.9%). These two deprivation outcomes, both relatively mild and often reversible, jointly contribute to over 80 percent of the first hardship experiences. The prominence of bill-payment difficulty as the primary landing form has a clear policy relevance. That is, an observation of utility arrear can be used as an early-warning signal. Intervention triggered at this stage are likely to be more effective than responses initiated after hardship has intensified and escalated when exit probabilities are substantially lower, consistent with the policy evidence in poverty literature (Jenkins & Rigg, 2001; OECD, 2020).

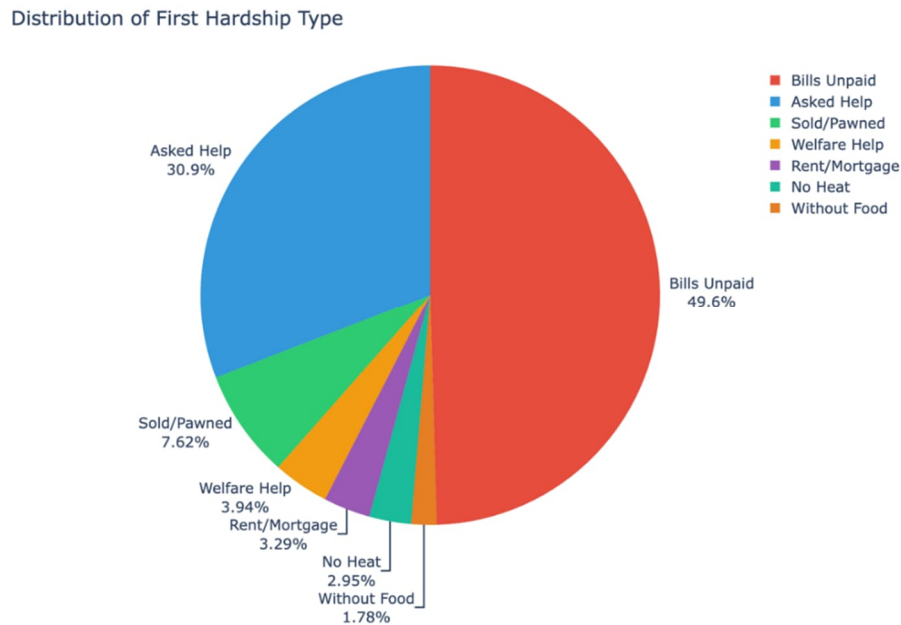
Table 5 Distribution of hardship spells by the landing form

First hardship	Events count	As percent of total spells	Spell duration
Any Hardship	23,547	100%	4.62
Bills unpaid	11,668	49.55%	3.52
Asked help	7,269	30.87%	4.05
Sold/Pawned	1,794	7.62%	4.35
Welfare help	928	3.94%	4.77
Rent/Mortgage	775	3.29%	3.67
No heat	694	2.95%	4.11
Without food	419	1.78%	4.01

In contrast, more severe manifestations such as rent or mortgage arrears, food insecurity, and energy poverty rarely emerge as the first hardship episodes. Recall in the summary statistics reported in Table 1, *Bills Unpaid* and *Asked Help* observations represent only 20.4% and 11.5% of the total sample, respectively, their heavier weight in landing form observations suggest that hardship experiences typically start in a mild form with households having informal coping responses, before some households slipping into deeper material

deprivations. These findings are consistent with the literature (Bane & Ellwood, 1986; Stevens, 1999), suggesting that severe depreciations in cross-section data seldom appear as initial failure when examined over time.

Figure 1: Distribution of landing event across seven forms of hardship



Referring to the last column in table 5, households in hardship has an average spell duration of 4.62, while there are notable differences in the average durations across the spells started in different forms. Within the survival framework, spell duration is defined as the length of time a household remains in the non-hardship state before experiencing an entry event, or until the end of observation if no entry occurs (right-censoring). All duration measures are therefore interpreted as time-to-entry, not the length of hardship itself.

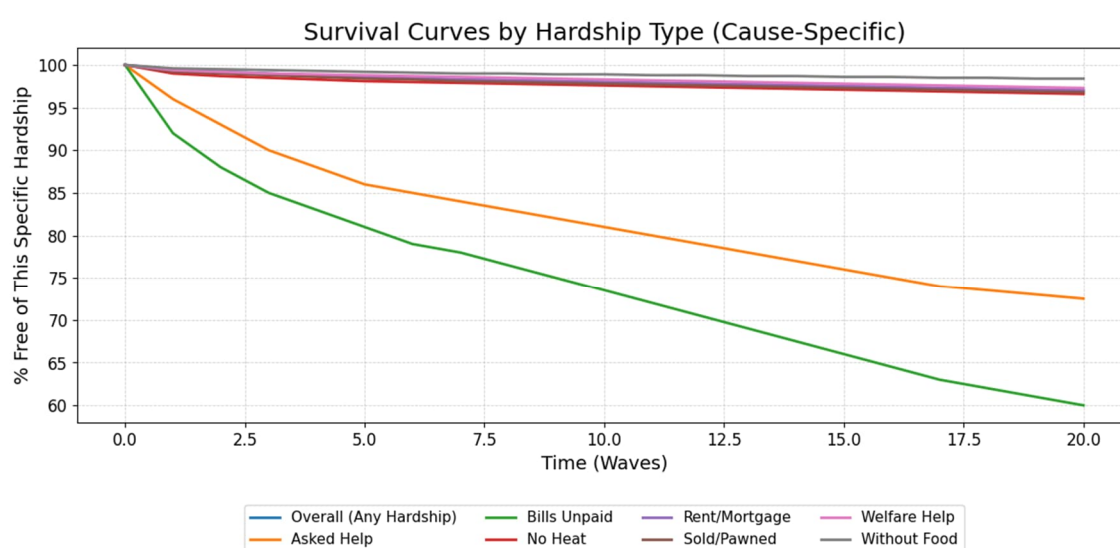
Households whose initial hardship involves *Bills Unpaid* exit faster with an average duration of 3.52 survey waves, suggesting the most common first-entry hardship type is also the most transitory form of hardship. Hardships started with rent or mortgage payment difficulties has an average duration of 3.67 survey waves, which is nevertheless a faster exit than those of the five other landing forms. In contrast, more severe deprivation outcomes, such as inability to heat home (4.11 waves) and going without meals (4.01 waves), are associated with longer hardship spells than payment arrears. Importantly, recovery is substantially slower when the first hardship involves *Welfare Help* or *Sold/Pawned* possessions which signal deeper material strain. These households have average durations of 4.77 and 4.35 survey waves, respectively. Therefore, there is a clear ranking in exit speed: households experiencing liquidity-related hardships exit fastest, while those entering hardship through asset depletion or

welfare reliance face substantially longer spells. These results highlight the difficulty of recovery once households transition from private coping mechanisms to formal support.

Next, we analyse how long households remain at risk before entering hardship in a specific form. We analyse the survival time and hazard ratio of hardship spells estimated within a cause-specific survival framework, where the occurrence of each alternative hardship forms is treated as a censoring risk event. Figure 2 illustrates the timing of inflow to hardship spells by different landing forms.

The downward sloping survival curves in Figure 2 show substantial heterogeneity across different forms of hardship at landing. Entering hardship spells with *Bill Unpaid* exhibits the fastest decline in survival rates. About 10 percent of households started to encounter difficulty in bill payments within two years (90% survived the first two years). The survival rate declines steadily thereafter to around 63 per cent by the 20th year, indicating that more than one third of households started to enter a hardship spell starting with having bill-payment problems, making it the dominant landing form of hardship.

Figure 2: Survival curves by the landing form



Hardships starting with *Asked Help* follows a more moderate trajectory. Survival rates exceed 95 percent in the first year, then decrease gradually over time, reaching roughly 73 percent by the 20th year. In contrast, most households have survived the more severe forms of deprivation over extended periods, with *Without Food* showing the slowest survival decay - about 99 percent of household are free of this hardship in the first five years while the survival rate remains above 96 percent in the 20th year. *Rent/Mortgage* payment difficulties display similar pattern of steadily high survival rates. These results are consistent with the results discussed earlier.

Table 6 Cause-specific Cox HR estimates: landing analysis by the first form

Dependent variable	Bills Unpaid	Asked Help	Sold/Pawned	Welfare Help	Rent/Mortgage	No Heat	Without Food
Age	0.998* (0.001)	0.986*** (0.001)	0.999 (0.001)	1.000 (0.000)	1.002*** (0.000)	1.002*** (0.000)	0.999* (0.000)
Female	1.092*** (0.019)	1.077*** (0.019)	0.942*** (0.016)	1.009 (0.011)	1.019 (0.012)	1.006 (0.011)	0.981* (0.008)
Married	0.903*** (0.019)	0.821*** (0.018)	0.946*** (0.016)	0.962*** (0.011)	1.019 (0.012)	0.970** (0.010)	0.942*** (0.008)
Employed	0.881 (0.277)	0.694 (0.351)	1.149*** (0.029)	0.752 (0.333)	1.078*** (0.017)	1.043*** (0.011)	1.032*** (0.007)
Log Income	0.943*** (0.008)	0.945*** (0.009)	0.986 (0.009)	0.971*** (0.007)	0.991 (0.006)	0.978*** (0.007)	0.993* (0.003)
Family Size	1.066*** (0.006)	1.016** (0.006)	0.995 (0.005)	0.992* (0.004)	1.004 (0.004)	0.992** (0.003)	0.992** (0.003)
Hours Worked	1.000 (0.001)	0.996*** (0.001)	1.000 (0.001)	0.999*** (0.000)	1.001 (0.000)	0.999** (0.000)	0.999* (0.000)
Postgraduate	0.709*** (0.042)	0.877** (0.044)	0.910** (0.031)	0.984 (0.027)	0.937* (0.026)	0.989 (0.024)	0.964** (0.014)
Graduate	0.767*** (0.043)	0.960 (0.039)	0.965 (0.038)	0.972 (0.025)	0.947* (0.024)	1.046 (0.030)	0.975 (0.015)
Diploma	0.748*** (0.025)	0.998 (0.024)	0.942** (0.020)	0.969* (0.015)	0.973 (0.016)	0.953*** (0.011)	0.985 (0.011)
Bachelor Degree	0.931* (0.031)	0.990 (0.032)	1.035 (0.032)	1.012 (0.020)	1.029 (0.023)	1.007 (0.018)	0.980 (0.013)
Certificate	1.195*** (0.021)	0.981 (0.020)	1.055** (0.019)	1.003 (0.012)	1.040** (0.015)	1.032* (0.013)	1.007 (0.010)
Year 12	0.966 (0.024)	1.121*** (0.023)	0.988 (0.020)	0.993 (0.013)	0.982 (0.014)	0.995 (0.012)	1.018 (0.012)
Own with Mortgage	1.422*** (0.019)	1.221*** (0.019)	1.025 (0.015)	1.029* (0.011)	1.032* (0.013)	1.002 (0.010)	1.036*** (0.009)
Renting (Public Housing)	2.079** (0.236)	1.318 (0.260)	1.039 (0.238)	1.582 (0.365)	0.884*** (0.026)	0.937*** (0.015)	1.681 (0.554)

Table 6 (continued)

	Bills Unpaid	Asked Help	Sold/Pa wned	Welfare Help	Rent/M ortgage	No Heat	Without Food
Renting	1.117*	1.106	1.004	1.075	0.942*	1.025	0.992
(Private)	(0.054)	(0.054)	(0.048)	(0.041)	(0.027)	(0.035)	(0.022)
Fired/Redun dant	0.976*	1.065 ***	1.080 ***	1.036 ***	1.036 ***	1.037 ***	1.045***
	(0.011)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)
Serious Illness	0.991	1.033*	1.061 ***	1.027**	1.025**	1.025 **	1.045***
	(0.014)	(0.013)	(0.010)	(0.009)	(0.009)	(0.008)	(0.007)
Death in	1.025**	1.082 ***	1.087 ***	1.040 ***	1.039 ***	1.037 ***	1.046***
Family	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)
Victim of	1.003	1.063 ***	1.077 ***	1.041 ***	1.029**	1.040 ***	1.045***
Violence	(0.010)	(0.010)	(0.009)	(0.008)	(0.009)	(0.007)	(0.006)
Member	1.028 ***	1.080 ***	1.084 ***	1.040 ***	1.038 ***	1.039 ***	1.046***
in Jail	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,250	32,250	32,250	32,250	32,250	32,250	32,250
Risk events	6,856	4,197	987	386	528	279	187
C-index	0.621	0.649	0.620	0.641	0.600	0.693	0.733

Note. This table reports hazard ratios from cause-specific Cox proportional hazards models estimated separately for each hardship type. Robust standard errors are reported in parentheses. All models include time-varying covariates where applicable and control for state fixed effects and survey wave fixed effects. Event counts report the number of first-entry hardship events for each model. The C-index measures model discrimination. Statistical significance is indicated by * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6 presents the results of cause-specific Cox model estimates for competing landing risks in seven different forms. For succinctness, we present the results for variable importance scores in Table A1 in Appendix reinforce these distinctions, showing that housing, education and employment factors are the primary source of discrimination for most landing types. Taken together, these results indicate that hardship entry combines common mechanisms with some form-specific risk profiles.

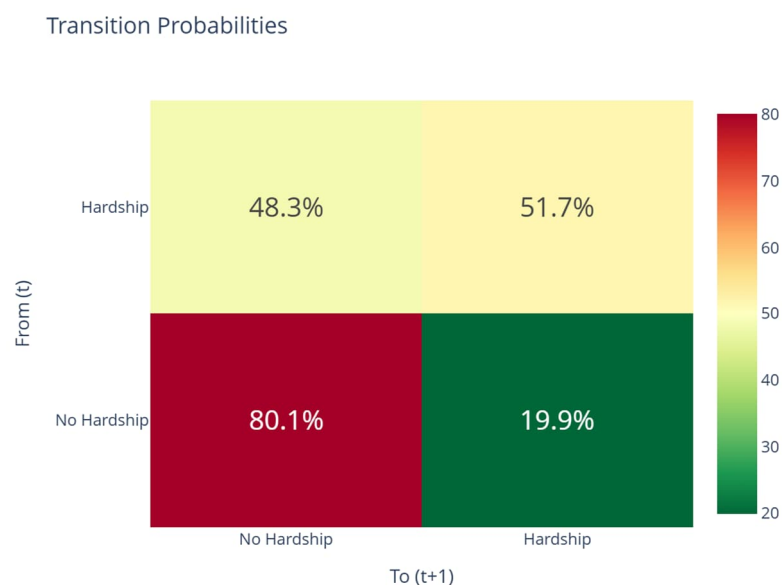
Referring to Table 6, education, marriage, and income are protective factors reducing hardship risk across various landing forms, consistent with the estimates for aggregate measure of *Any hardship* at landing. Mortgage arrear, job loss and significant adverse life events continue to increase hardship risk. However, the effects of female household-head, family size and rent arrears for both public and private housing households vary depending on the hardship form: as risk factors for mild forms (*Bills Unpaid* or *Asked Help*) but become protective factors for more severe forms such as rent arrear, unable to heat home, or went without food.

5.2 Persistence and comparative analysis of repeat spell entries

As previously discussed in Section 5.1, households slipped into hardship are trapped in a spell for 4.62 survey waves on average, indicating widespread persistence of hardship. This section is devoted to formal statistical analysis to examine whether hardship tends to persist once it occurs.

Figure 3 illustrates the state transition matrix over a period of two consecutive years. The results reveal pronounced asymmetry between the persistence of hardship state versus that of the non-hardship state. In any given year, households in non-hardship state have 19.9% probability of experiencing hardship in the following year. By contrast, the households in hardship this year have a 51.7% probability of staying in hardship the next year – a probability that is more than 2.6 times higher than the peer group (51.7% versus 19.9%). This result reflects a dynamic mechanism whereby hardship itself erodes households' capacity to recover, consistent with cumulative disadvantage processes observed in other domains of social risk.

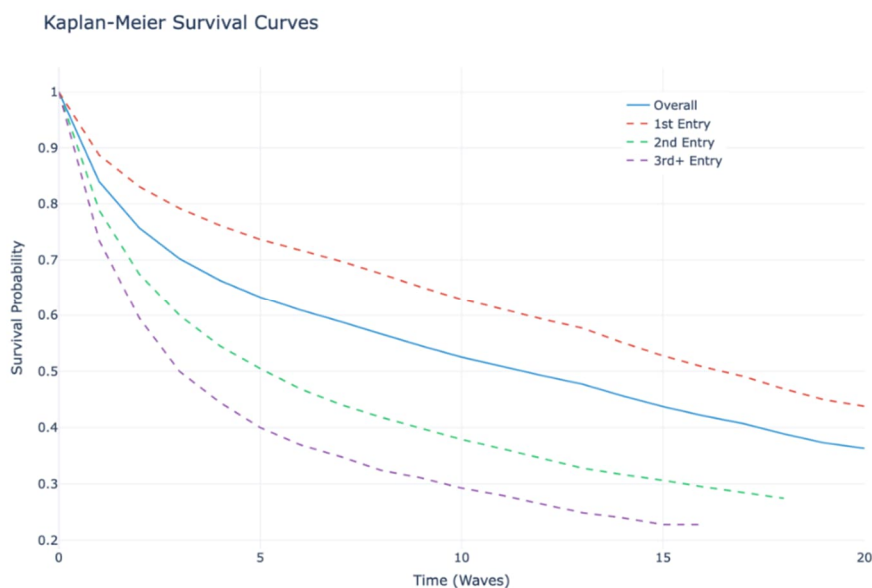
Figure 3 State transition matrix from time t (row state) to $t+1$ (column state)



Next, we investigate whether recurrent hardship spells have different characteristics. Figure 4 illustrates the survival rate curves for all hardship spells, and the spells in sub-sample groups of Entry1, Entry2 (one prior spell) and Entry3+ (two or more preceding spells). Recall from Table 1, the event counts for repeat spells become progressively smaller: 43,784 observations for the Entry1 group, 15,330 for Entry2, and 11,565 for Entry3+. The Overall sample aggregates the samples in these groups.

In Figure 4, the downward sloping survival curves indicate that the risk of experiencing hardship increases over time. The survival curve of the Overall sample shows that approximately 63% of the households remain hardship-free after five survey waves, while the survival rate declines to 52% after ten survey waves and further reduced to about 36% by the 20th survey. However, the shape of survival curves for different sub-sample groups are different, indicating differences in how fast the rate of hardship occurs for different orders of Entry number. For Entry1 spells, more than three quarters of households remain in no-hardship state after five years, and more than half are still hardship-free after 15 years. In the Entry2 hardship spells sample, we observe a faster increase in the rate of hardship events over the short term, with survival rates quickly reduced to about 50 percent in five years and about 30 percent in 15 years. In comparison, the survival curve decays even faster for spells in the Entry3+ sub-sample which shows an event rate of 50 percent in about three years while less than 30 percent of the samples remain free from hardship in year ten. Unfortunately, few households in this group can remain hardship-free if followed over a sufficiently long horizon.

Figure 4: Hazard rates by entry number



We perform the Cox PH model analysis for the initial and repeated entries of hardship spells and present the results in Table 7. The variable importance scores are reported in Table A2 in Appendix. The model performance measure, C-index values, are close to 0.6, suggesting that these household characteristics perform well in predicting the hazard ratios of hardship at different entry levels.

Comparing the hazard ratio estimates across different entry numbers reported in Table 7, we observe both continuity and attenuation. Education, marriage, and income remain the most influential protective characteristics across all entry levels. At the same time, housing factors, female household head, and family size are influential risk factors across all entry numbers. For example, households in private residencies with mortgages have between 24.7 and 43.7 percent (HR = 1.247, 1.294 and 1.437 for Entry #+, Entry2, and Entry1 groups, respectively) higher risk than those own their homes outright. On the other hand, job loss and adverse life events increase the risk of initial hardship, while their effects diminish for repeat spells.

A notable pattern observed from Table 7 and Table A2 is the declining role of human capital and traditional social buffers. Education, marital status and income show more protective effect against the entry to an initial spell, reflecting their role in preventing initial hardship. However, their strength and relative importance are reduced for repeat spells. For example, having a bachelor's degree offers a risk-reduction benefit of 23.3 percent (HR = 0.767) against entering a hardship spell the first time. However, for households having a previous spell, the protective effect is reduced to 17.5 percent (HR = 0.825). A possible explanation is that households appearing in the second or later entries have already passed through these initial layers of protection, leaving their risk increasingly shaped by dynamic or unobserved vulnerabilities; consistent with the dynamic selection argument in the literature as (Heckman, 1981; Stevens, 1999).

Interestingly, while job loss remains a significant risk factor across entry levels, its role switches from a protection factor against the risk of first entry (HR = 1.057) to a risky factor which increases the risk of repeated spells (HR = 0.911 for Entry2, and 0.880 for Entry3+). From Table A2, while income remains a statistically significant risk protection factor, its relative importance declines sharply in later spells, falling from 0.114 at the first entry to 0.050 at the second entry. This suggests that although income continues to buffer risk, it no longer serves as the primary discriminator among households once hardship becomes recurrent.

Table 7 Cox HR estimate by entry number

	Entry1	Entry2	Entry3+
Age	0.990*** (0.001)	0.996*** (0.001)	0.998 (0.001)
Female	1.074*** (0.020)	1.067* (0.026)	1.113*** (0.031)
Married	0.825*** (0.021)	0.894*** (0.028)	0.884*** (0.033)
Employed	0.613 (0.417)	0.545 (0.423)	1.283 (0.480)
Log Income	0.892*** (0.012)	0.951*** (0.011)	0.925*** (0.015)
Family Size	1.065*** (0.007)	1.039*** (0.009)	1.055*** (0.011)
Hours Worked	0.999 (0.001)	0.997** (0.001)	0.998 (0.001)
Postgraduate	0.675*** (0.049)	0.754*** (0.066)	0.758*** (0.073)
Graduate Diploma	0.793*** (0.044)	0.876* (0.063)	0.835* (0.073)
Bachelor Degree	0.767*** (0.027)	0.825*** (0.039)	0.841*** (0.046)
Diploma	0.912** (0.036)	1.000 (0.047)	0.978 (0.051)
Certificate	1.098*** (0.024)	1.146*** (0.031)	1.048 (0.034)
Year 12	0.971 (0.027)	1.023 (0.034)	0.949 (0.041)
Own with Mortgage	1.437*** (0.022)	1.294*** (0.027)	1.247*** (0.032)
Renting (Public Housing)	2.189*** (0.225)	2.030* (0.280)	2.362* (0.340)
Renting (Private)	1.202** (0.066)	1.146 (0.078)	0.958 (0.083)
Fired/Redundant	1.057*** (0.013)	0.911** (0.033)	0.880*** (0.036)
Serious Illness	0.979 (0.020)	0.964 (0.037)	0.941 (0.039)
Death in Family	1.094*** (0.011)	0.979 (0.027)	1.049 (0.029)
Victim of Violence	1.032* (0.015)	0.984 (0.033)	0.976 (0.035)
Family Member in Jail	1.100*** (0.010)	0.993 (0.025)	1.003 (0.028)
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	16,491	8,620	7,139
Events count	6,107	4,062	3,251
C-index	0.645	0.598	0.592

Note. The coefficients represent hazard ratios which are converted from the original coefficient estimates. Robust standard errors are reported in parentheses. State and survey wave fixed effects are controlled for. Observations and events refer to household-year spells at risk of entry. The C-index reports model discrimination. Statistical significance is indicated by * $p < .10$, ** $p < .05$, *** $p < .01$.

Moreover, employment status is enlisted as the second most important predictor in Table A2. However, the hazard ratio estimates for *Employment* reported in Table 7 are not statistically significant at the conventional critical levels, suggesting that these estimated values cannot be distinguished from zero with confidence. This finding contrasts with the evidence reported by Brown et al. (2014) for British households.

To summarise, households with prior hardship experience are substantially more likely to enter repeat episodes of hardship, and to do so sooner, than households with limited or no prior hardship experience. First-time hardship is more heavily influenced by socioeconomic and demographic characteristics. As hardship spells repeat, housing constraints and accumulated vulnerability become increasingly decisive. However, the discriminating power of income and human capital weakens. These findings provide new empirical support for the argument that post-hardship interventions must extend beyond short-term income support, and provide more support for housing, employment and gender equality. Without addressing structural constraints, particularly in housing and education, policies are unlikely to break the cycle of recurrent hardship once state dependence has taken hold.

6. Conclusions

This paper studies household financial hardship as a dynamic process, examining how hardship emerges, persists, repeats, and is affected by various household characteristics. Based on the longitudinal data from 22 waves of the HILDA Survey since its inception, we find that financial hardship is a dynamic and cumulative process rather than a one-off shock.

Hardship rarely begins with severe forms of deprivations: 49.6% of the first hardship episodes involve difficulty in bill payments while 30.9% of hardship spells started with reliance on financial help from family or friends. Recovery period varies across the spells started in different forms. Spells landing on more severe forms like welfare dependence take longer to recover than those starting in relatively mild forms, such as difficulty paying bills.

Burdens of rent and mortgage are dominant risk factors, which are both economically and statistically significant. The risk of rent arrears of public housing households is more than doubled comparing to those who own their family homes outright. Other significant risk factors include households headed by female, bigger family size, job loss, and severe adverse life events. On the other hand, education, income, and marriage provide consistent protection against falling into hardship.

On average, households in the no-hardship state have a 19.9% probability of transitioning into hardship in the following year. In contrast, households already experiencing

hardship are substantially more likely to remain in hardship, with 51.7% continuing to experience hardship the next year, implying significant persistence and state dependence in hardship experience. Furthermore, households with prior hardship spells have elevated risk of entering new spells, and to do so sooner, than households with less or no prior hardship experience.

To summarise, financial hardship often begins with relatively mild forms of deprivation before escalating in severity and accumulating to become entrenched. Recovery becomes increasingly difficult as hardship episodes lengthen or recur. These results support a policy perspective that views hardship not merely as a condition to be alleviated, but as a trajectory to be interrupted before it becomes self-reinforcing (Heckman, 2006). Consistent with recent policy discussions on early intervention and social risk prevention (World Bank, 2018), timely intervention can reduce the need for more intensive and costly forms of assistance at later stages. Therefore, effective policy responses should focus on early detection and intervention, while simultaneously tackling the structural drivers of hardship, particularly housing affordability, access to education, and job security.

A limitation of this research is that we rely on the hardship data based on self-reported observations which may be affected by recall error or social desirability. Future research could evaluate the effectiveness of early-intervention programs designed to respond to initial signs of material distress.

Appendix

Table A1 Variable importance ranking by hardship type

	Bills Unpaid	Asked Help	Sold/ Pawned	Welfare Help	Rent/ Mortgage	No Heat	Without Food
Renting (Public Housing)	0.7321	0.2761	0.0378	0.4585	0.1232	0.0648	0.5193
Own with Mortgage	0.3522	0.1999	0.0249	0.0290	0.0319	0.0020	0.0349
Postgraduate	0.3441	0.1316	0.0938	0.0164	0.0650	0.0116	0.0369
Bachelor Degree	0.2908	0.0024	0.0602	0.0319	0.0272	0.0484	0.0151
Graduate Diploma	0.2652	0.0404	0.0354	0.0285	0.0549	0.0448	0.0248
Certificate	0.1778	0.0189	0.0534	0.0029	0.0396	0.0319	0.0074
Employed	0.1265	0.3648	0.1392	0.2845	0.0754	0.0418	0.0316
Renting (Private)	0.1103	0.1009	0.0038	0.0723	0.0599	0.0249	0.0077
Married	0.1018	0.1973	0.0552	0.0384	0.0190	0.0309	0.0598
Female	0.0878	0.0739	0.0593	0.0087	0.0184	0.0064	0.0188
Family Member in Jail	0.0275	0.0772	0.0809	0.0395	0.0371	0.0384	0.0454
Death in Family	0.0244	0.0788	0.0836	0.0396	0.0379	0.0368	0.0447
Fired/Redundant	0.0239	0.0633	0.0773	0.0357	0.0349	0.0366	0.0441
Serious Illness	0.0093	0.0323	0.0589	0.0266	0.0248	0.0247	0.0442
Victim of Violence	0.0032	0.0615	0.0741	0.0399	0.0285	0.0393	0.0442

Note. Importance scores are reported for household characteristics (covariates), listed in the descending order of the scores in column 2. Each score measures a covariate's contribution to model discrimination for the corresponding hardship-specific Cox model, computed from the full model specification for each hardship type and reflect relative, not causal, importance. Higher values indicate greater contributions.

Table A2 Variable importance by entry spell number

	Entry1	Entry2	Entry3+
Renting (Public Housing)	0.7833	0.7080	0.8593
Employed	0.4889	0.6063	0.2493
Postgraduate	0.3935	0.2820	0.2773
Own with Mortgage	0.3622	0.2581	0.2207
Bachelor Degree	0.2647	0.1919	0.1732
Graduate Diploma	0.2324	0.1330	0.1801
Married	0.1920	0.1122	0.1238
Renting (Private)	0.1839	0.1366	0.0433
Log Income	0.1139	0.0499	0.0775
Certificate	0.0931	0.1359	0.0471
Death in Family	0.0895	0.0207	0.0483
Female	0.0713	0.0646	0.1075
Family Size	0.0628	0.0384	0.0531
Fired/Redundant	0.0550	0.0927	0.1283
Serious Illness	0.0207	0.0364	0.0608

Note. Importance scores are reported for household characteristics (covariates), listed in the descending order of the scores in column 2. Each score measures a covariate's contribution to model discrimination for the corresponding hardship-specific Cox model, computed from the full model specification for each hardship type and reflect relative, not causal, importance. Higher values indicate greater contributions.

References

Andersen, P. K., & Gill, R. D. (1982). Cox's regression model for counting processes: A large sample study. *The Annals of Statistics*, 10(4), 1100-1120.

Australian Bureau of Statistics (ABS). (2026, June). *Selected living cost indexes, Australia*. <https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/selected-living-cost-indexes-australia/latest-release>

Bane, M. J., & Ellwood, D. T. (1986). Slipping into and out of poverty: The dynamics of spells. *Journal of Human Resources*, 21(1), 1–23. <https://doi.org/10.2307/145955>

Berthoud, R., & Bryan, M. (2011). Income, deprivation and poverty: A longitudinal analysis. *Journal of Social Policy*, 40(1), 135–156. <https://doi.org/10.1017/S0047279410000407>

Berthoud, R., & Kempson, E. (1992). *Credit and debt: The PSI report*. Policy Studies Institute. <https://www.bristol.ac.uk/geography/research/pfrc/themes/credit-debt/credit-debt.html>

- Beverly, S. G. (2001). Material hardship in the United States: Evidence from the Survey of Income and Program Participation. *Social Work Research*, 25(3), 143–151. <http://www.jstor.org/stable/42659462>
- Bhutta, N., & Dettling, L. J. (2018). Money in the bank? Assessing families' liquid savings using the Survey of Consumer Finances. *Journal of Economic Perspectives*, 32(2), 219–240. <https://doi.org/10.1257/jep.32.2.219>
- Bourova, E., Ramsay, I., & Ali, P. (2019). The experience of financial hardship in Australia: Causes, impacts and coping strategies. *Journal of Consumer Policy*, 42(2), 189–221. <https://doi.org/10.1007/s10603-018-9392-1>
- Breunig, R., & Cobb-Clark, D. A. (2005). Income inequality and social welfare: Evidence from Australia. *Economic Record*, 81(253), 273–290. <https://doi.org/10.1111/j.1475-4932.2005.00264.x>
- Brown, S., Ghosh, P. & Taylor, K. (2014). The existence and persistence of household financial hardship: A Bayesian multivariate dynamic logit framework, *Journal of Banking & Finance*, 46, 285–298. <https://doi.org/10.1016/j.jbankfin.2014.05.022>
- Butterworth, P., Olesen, S. C., & Leach, L. S. (2012). The role of hardship in the association between socio-economic position and depression. *Australian & New Zealand Journal of Psychiatry*, 46(4), 364–373. <https://doi.org/10.1177/0004867411433215>
- Butterworth, P., Rodgers, B., & Windsor, T. D. (2009). Financial hardship, socio-economic position and depression: Results from the PATH Through Life Survey. *Social science & medicine*, 69(2), 229–237. <https://doi.org/10.1016/j.socscimed.2009.05.008>
- Cantó, O. (2002). Climbing out of poverty, falling back in: Low income stability in Spain. *Applied Economics*, 34(15), 1903–1916. <https://doi.org/10.1080/00036840210129392>
- Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society: Series B (Methodological)*, 34(2), 187–220.
- Harrell, F. E. (2015). *Regression modeling strategies: With applications to linear models, logistic and ordinal regression, and survival analysis* (2nd ed.). Springer.
- Heckman, J. J. (1981). Heterogeneity and state dependence. In S. Rosen (Ed.), *Studies in labor markets* (pp. 91–139). University of Chicago Press.
- International Monetary Fund (IMF) (September 2025). Global Debt Database - Household debt, loans and debt securities: Percent of GDP. Available from <https://www.imf.org/external/datamapper/datasets/GDD>
- Jenkins, S. P., & Rigg, J. A. (2001). *The dynamics of poverty in Britain* (Department for Work and Pensions Research Report No. 157). Department for Work and Pensions.
- Kiefer, N. M. (1988). Economic duration data and hazard functions. *Journal of Economic Literature*, 26(2), 646–679.

- Marshall, G. Tucker-Seeley, R. (2018). The association between hardship and self-rated health: does the choice of indicator matter?. *Annals of Epidemiology*, 28(7), 462-467. <https://doi.org/10.1016/j.annepidem.2018.03.013>.
- Mayer, S. E., & Jencks, C. (1989). Poverty and the distribution of material hardship. *Journal of Human resources*, 88-114. <https://www.jstor.org/stable/145934>
- Nolan, B., & Whelan, C. T. (2011). *Poverty and deprivation in Europe*. Oxford University Press.
- OECD. (2020). *Preventing ageing unequally*. OECD Publishing. <https://doi.org/10.1787/9789264249492-en>
- Pilkaskas, N. V., Currie, J. M., & Garfinkel, I. (2012). The great recession, public transfers, and material hardship. *Social Service Review*, 86(3), 401-427. <https://doi.org/10.1086/667993>
- Saunders, P., & Adelman, L. (2004). *Evaluating the adequacy of social security payments* (Discussion Paper). Social Policy Research Centre.
- Stevens, A. H. (1999). Climbing out of poverty, falling back in: Measuring the persistence of poverty over multiple spells. *Journal of Human Resources*, 34(3), 557–588. <https://doi.org/10.2307/146380>
- Thomas, M.M.C. (2022). Longitudinal Patterns of Material Hardship Among US Families. *Social Indicators Research*, 163, 341–370. <https://doi.org/10.1007/s11205-022-02896-8>
- Turunen, E., & Hiilamo, H. (2014). Health effects of indebtedness: A systematic review. *BMC Public Health*, 14, 489. <https://doi.org/10.1186/1471-2458-14-489>
- Wooden, M., Watson, N., & Butterworth, P. (2024). Data resource profile: Household, Income and Labour Dynamics in Australia (HILDA) Survey. *International Journal of Epidemiology*, 53(2). <https://doi.org/10.1093/ije/dyae043>
- World Bank. (2018). The State of Social Safety Nets 2018. Washington, DC: World Bank. <https://www.worldbank.org/en/topic/socialprotectionandjobs/publication/the-state-of-social-safety-nets-2018>