The effect of mental health on early retirement decisions: Evidence from Australia

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Abstract

Health and labour supply are interconnected; However, research has predominantly focused on the impact of physical health, leaving a gap in understanding the role of mental health problems. This study addresses this gap by examining the effect of mental health on early retirement decisions using data from the Household, Income, and Labour Dynamics in Australia (HILDA) Survey. We use both linear probability models and a discrete-time hazard approach. While linear models estimate the average effect, the discrete-time hazard model tracks initially employed individuals aged 50 to 64 over time until they retire early or reach retirement age. To mitigate potential bias arising from the timing of reporting of mental health and retirement decisions, lagged measures of mental health are applied, with respect to the temporal sequence of events. To address measurement bias, the association between our derived mental health variable and other objective psychiatric measures is examined. Furthermore, we include the death of a close friend as an instrument for mental health status, helping us validate and strengthen causal findings of our study. Lastly, we examine whether unobserved heterogeneity poses a problem in our analysis by estimating models with and without unobserved heterogeneity. Our findings indicate a significant and positive causal impact of poor mental health on early retirement decisions, which is also supported by the nonlinear analysis. To explore potential gender heterogeneity, separate analyses are conducted for males and females. The observed differences in the results between the two groups support the assumption of gender-specific effects. These findings suggest that poor mental health has a significant and potentially causal impact on premature exit from the labour market, particularly among men. The results highlight the importance of effective mental health management in supporting longer working lives.

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Introduction

Mental health issues represent a growing concern for labour markets worldwide, significantly influencing employment outcomes across sectors. Poor mental health affects labour market participation through several channels. Affected individuals may experience increased absenteeism due to illness, medical appointments, or treatment regimens (Bloom and Canning 2000). Symptoms, such as depression or mood instability, can impede regular work attendance and reduce motivation to invest in human capital (Fadare *et al*. 2023, Tompa 2002). The resulting decline in labour productivity and economic engagement may encourage earlier retirement, particularly if individuals anticipate a reduced lifespan and wish to maximise leisure time from accumulated wealth. Additionally, presenteeism, or diminished productivity while at work, may further erode performance, ultimately leading to premature labour market exit (Chatterji *et al*. 2007). Mental health problems may also increase reliance on non-wage income sources, such as welfare benefits, thereby potentially reducing the financial incentive to remain employed (Disney *et al*. 2006). However, this relationship is not uniform; some individuals may instead choose to remain in employment longer in order to meet elevated healthcare expenses associated with managing chronic mental health conditions (Bryan *et al*. 2022, Frijters *et al*. 2010, Ngui *et al*. 2010, Hamilton *et al*. 1997).

In Australia, the economic burden of poor mental health is substantial. Estimates by the Australian Bureau of Statistics suggest that mental health-related work absences cost approximately AU$60 billion annually (Australian Bureau of Statistics 2008). Furthermore, Lee *et al*. (2017) estimated that productivity losses stemming from depression, anxiety disorders, and substance use disorders amounted to AU$11.8 billion in 2007, with additional fiscal implications of AU$1.2 billion in lost income tax revenue and AU$12.9 billion in welfare expenditures. For individuals diagnosed with psychosis, Neil *et al*. (2014) calculated productivity losses at AU$40,941 per person, with further indirect costs, such as those associated with supported employment and non-governmental services, totalling an additional AU$14,642 per person.

This paper makes three key contributions to the literature on mental health and labour supply. First, it tries to provide causal evidence on the effect of mental health on early retirement decisions among older individuals in Australia, addressing an underexplored area in comparison to the well-established literature on physical health and labour market exits. Mental health conditions, often less visible than physical ailments, may receive disparate treatment from employers and policymakers (Ngui *et al*. 2010). For example, in a similiar economy, the United Kingdom, one in four people reported a mental disorder in 2016 (Alderwick and Dixon 2019, McManus *et al*. 2016), yet the National Health Service allocated only 12.5 per cent of its total budget to mental health in 2017/18, with a target of 16.2 per cent by 2022/23 (Baker & Kirk-Wade 2023).

As Australia's population ages, with those over 50 projected to increase from 12 per cent to 22 per cent between 2015 and 2050 (World Health Organization 2022), understanding the causes of early retirement becomes critical for economic planning.

An ageing workforce can strain public finances and healthcare systems, increase dependency ratios, and necessitate adjustments to retirement policies (Liddiard 1978). Determining whether early retirement is driven by health or financial considerations has significant implications for public policy (Frijters *et al*. 2 010). Distinguishing mental from physical health conditions helps in targeting interventions and tailoring incentive schemes that can prolong workforce participation.

To investigate the causal relationship between mental health and early retirement, the empirical analysis proceeds in two stages. First, a linear cross-sectional framework is applied, beginning with Ordinary Least Squares (OLS) estimation and followed by a Two-Stage Least Squares (2SLS) specification. The 2 SLS model uses the lagged death o f a close friend as an instrument for mental health. Unlike the more commonly used death of a family member, which may directly affect retirement through caregiving or financial implications, this instrument is assumed to influence mental health without directly impacting retirement decisions, helping to address endogeneity in a transparent and interpretable way.

To establish a benchmark and enable meaningful comparisons, we begin by estimating a linear probability model. This serves as a baseline against which the results of subsequent nonlinear analyses can be assessed. Although linear models are intuitive and straightforward, they impose restrictive assumptions and may yield biased estimates. Nonlinear analysis offers an additional framework for modelling time-to-event outcomes like retirement, as it accounts for the dynamic nature of such decisions and handles censoring more appropriately.

The second contribution to the literature, and the second stage of the analysis, extends the investigation using discrete-time hazard models to examine the timing of retirement while explicitly addressing whether unobserved heterogeneity is an issue in our analysis. This approach compares models with and without unobserved heterogeneity, under various distributional assumptions, to assess the robustness of the results. Specifically, a discrete-time hazard model is paired with a two-stage residual inclusion (2SRI) estimator to control for both endogeneity and unobserved confounding (Terza *et al*. 2008). This more flexible methodology allows for testing whether linear models provide adequate estimates or if failing to account for unobserved heterogeneity and nonlinearity introduces bias, especially when unmeasured factors such as personality traits or job satisfaction may simultaneously influence mental health and retirement decisions.

By leveraging panel data within the discrete-time hazard framework, the longitudinal structure captures individual dynamics over time. While the discrete-time model assumes selection on observables, i.e., that mental health only affects retirement through measured variables, this assumption may be violated if unobserved factors influence both outcomes. To address this, the 2SRI procedure improves causal inference by mitigating bias from such confounding in a panel data setting.

Lastly, the paper explores the role of measurement error and reporting bias in mental health assessment. Unlike many existing studies that rely exclusively on self-reported mental health status, this study compares subjective and objective indicators to account for potential biases in reporting. Social desirability or stigma may lead respondents to underreport psychological conditions, which can result in attenuated estimates of the true effects (Bharadwaj *et al*. 2017, Brohan and Thornicroft 2010, Rüsch *et al*. 2005). By triangulating different data sources and validating mental health measures, the analysis seeks to provide more robust and credible findings.

The results reveal a statistically significant association between poor mental health and an increased likelihood of early retirement. The instrumental variable analysis supports a causal interpretation, with the death of a close friend serving as a valid and relevant instrument, as indicated by the first-stage statistics. When the analysis is extended to a longitudinal framework, the findings remain consistent, with the estimated effect of mental health on early retirement slightly larger than in the non-IV models. This pattern suggests that failing to address endogeneity may lead to an underestimation of the true impact of mental health.

The importance of correcting for endogeneity is further highlighted by the notably larger coefficient, more than six times greater, in the 2SLS model compared to the baseline OLS estimate. Moreover, accounting for unobserved heterogeneity in the longitudinal models does not substantially alter the results, with estimates remaining similar across models with and without frailty.

Importantly, the results indicate gender-specific differences in the mental health and retirement relationship. For males, poor mental health significantly increases the likelihood of early retirement across most specifications, whereas for females, the effect is weaker and not statistically significant in some models. These findings offer important insights for policymakers aiming to extend working lives, improve mental health support, and mitigate the fiscal challenges posed by an ageing population. This study contributes to the existing literature by providing robust evidence from Australia, applying rigorous econometric methods, and underscoring the significance of gender and measurement issues in mental health research.

The outline of the paper is as follows. The next section (section 2) presents a review of the existing literature that examines the impact of mental health on labour market outcomes and early retirement decisions. Section 3 describes the empirical methods, including linear probability model, two-stage least squares, discrete-time hazard models with and without unobserved heterogeneity, validity checks, and the inclusion of the two-stage residual inclusion approach within a discrete-time hazard model. This is followed by the data description in section 4. Section 5 presents the results, while section 6 contains the discussion and conclusion.

Background and Literature Review

Mental health disorders are diverse and vary in their symptoms, treatments, diagnosis, and outcomes (American Psychiatric Association 2013). The severity of mental illness varies greatly from common illnesses, such as general anxiety, mood swings, eating disorders, to more severe mental disorder e.g., schizophrenia. There is a wide range of literature within different fields of research that show mental health disabilities are linked to poorer labour market outcomes, in addition to affecting social life, such as terminating relationships, loneliness, and a greater likelihood of being involved in a crime (Bartel and Taubman 1979, 1986).

There is a substantial amount of previous research on the relationship between health and labour market outcomes, such as economic inactivity or retirement. However, most of the re-search focuses on the effect of physical or general health, without controlling for mental health specifically. Few papers which analyse the effect of mental health and labour market outcomes, such as employment status (Bryan *et al*. 2022, Chatterji *et al*. 2011, Frijters *et al*. 2010, Lu *et al*. 2009, Sainsbury *et al*. 2008, Alexandre and French 2001, Ettner *et al*. 1997), income (Chatterji *et al*. 2011, Ettner *et al*. 1997) and work hours (Ettner *et al*. 1997). Stern (1989) observed the effect of health on retirement decisions, while using longitudinal data and observing health using subjective measures.

The empirical analysis is grounded in the standard life-cycle labour supply framework, in which individuals allocate time between work, leisure, and health investment to maximise life-time utility (Grossman 1972). Within this framework, health, including mental health, affects both the utility derived from work and the productivity of labour. To empirically assess this relationship, we estimate baseline linear models (LPM and 2SLS) where employment status serves as a reduced-form representation of labour supply decisions, and mental health is treated as a potentially endogenous determinant of labour market participation.

Stern (1989) was one of the first to identify a negative and statistically significant effect of health on retirement and labour supply, suggesting that poor health leads to a reduced labour market participation. Similarly, Bryan *et al*. (2022) found that poor mental health decreases the probability of being employed, while Lu *et al*. (2009) reported that a decline in average mental health is associated with a significant reduction in both employment rates and annual income. Their findings also indicate that the mental health index has a positive and significant effect on the likelihood of being employed. Despite these contributions, recent studies have focused mainly on general labour market outcomes, with limited attention to older individuals and specific outcomes such as early retirement decisions, exceptions include the work of Zucchelli *et al*. (2007) and Disney *et al*. (2006), who specifically examine the effect of general health on labour market outcomes across older workers.

Previous studies of the effect of mental health on labour market outcomes, based mainly on cross-sectional data to examine this relationship (Zhang *et al*. 2009, Cai and Kalb 2007, Bound *et al*. 1999, Siddiqui and Ali Shah 1997, Bazzoli 1985). However, the use of cross-sectional data poses limitations in capturing the dynamic effects of health on labour supply and addressing the issue of possible endogeneity through unobserved personal characteristics. To overcome these limitations, longitudinal data has been recommended to mitigate selection bias and gain a deeper understanding of individual behaviour (Chatterji *et al*. 2011, Nerlove 2005).

The discrete-time hazard analysis, widely used in the biomedical field and more recently in health economics research, provides valuable insights into the impact of health on workforce outcomes (Bu¨nnings and Tauchmann 2015, Zucchelli *et al*. 2007, Disney *et al*. 2006). This approach offers several advantages. Firstly, it allows greater flexibility in modelling dynamics and exploring variations in the impact of health on labour market transitions according to current employment status (Disney *et al*. 2006). Secondly, it enables examination of the timing and sequencing of events, offering a more nuanced understanding of the process leading to early retirement. By modelling the transition probabilities over discrete-time intervals, we can capture the dynamic nature of the decision making process and account for changes in mental health status over time. Finally, the discrete-time hazard approach accommodates time-varying covariates, such as changes in mental health status, marital status, and other relevant factors, allowing for a more comprehensive analysis of the determinants of early retirement decisions.

Building on this methodological foundation, previous empirical studies using longitudinal data have shown that poor self-reported general health is strongly associated with early retirement among older adults (Zucchelli *et al*. 2007, Disney *et al*. 2006). For instance, Disney *et al*. (2006) and Zucchelli *et al*. (2007) apply discrete-time hazard models using the HILDA dataset, adopting a non-parametric approach to the hazard function. Our study extends this line of research by employing the same discrete-time hazard framework described by Jenkins (1995), but focusing specifically on mental health rather than general health. Furthermore, consistent with Disney *et al*. (2006), Jenkins (1997, 1995), we account for unobserved heterogeneity to ensure robust inference.

While the discrete-time hazard framework provides a powerful tool to analyse transitions into early retirement, it also brings to the forefront an important econometric concern, namely endogeneity. In studying the relationship between mental health and retirement, endogeneity may arise due to measurement error in self-reported health, the potential for reverse causality between mental health and labour market participation, or omitted variables correlated with both. Addressing this issue is crucial to ensure that estimated effects reflect a causal rather than merely associative relationship.

The issue of endogeneity in our study is particularly relevant due to the potential presence of unobserved characteristics and events associated with both mental health and early retirement decisions (Bryan *et al*. 2022). To mitigate potential endogeneity bias, our study draws on strategies that exploit exogenous variation in health. One common approach involves identifying health shocks that are plausibly independent of unobserved individual characteristics (Disney *et al*. 2006, Bound *et al*. 1999). In this study, we define a health shock by incorporating both lagged and initial-period health. By conditioning on initial health, the coefficient on lagged health can be interpreted as a deviation from an individual's underlying health stock (Disney *et al*. 2006), thereby helping to control for unobserved, time-invariant health-related heterogeneity (Jones 2009).

We also control for the latter to minimise omitted variable bias, as both mental and physical health can influence retirement decisions. Specifically, we construct a variable representing a negative physical health shock, defined as the difference between expected and actual self-reported physical functioning scores. Following Apouey *et al*. (2019), we create a binary indicator that takes the value of one when the observed decline in health is greater than one standard deviation relative to the individual's expected change in health status. This measure helps isolate mental health effects that are not merely reflections of concurrent changes in physical condition.

While exogenous shocks can reduce endogeneity, they may not fully eliminate it. To strengthen causal identification, instrumental variable (IV) techniques are widely employed in health and labour economics. The work by Angrist *et al*. (1996) establishes a comprehensive framework for identifying causal effects using IVs, outlining the necessary assumptions, such as relevance and the exclusion restriction, and the estimation techniques required for valid inference. This framework has since guided a broad range of empirical applications in health and labour economics, highlighting both the potential and the limitations of IV strategies, including issues of weak instruments, overidentification, and bias arising from unobserved confounding variables (Frijters *et al*. 2010, Wooldridge 2010, Angrist and Pischke 2009, Zhang *et al*. 2009, Terza *et al*. 2008, Alexandre and French 2001, Ettner *et al*. 1997, Hamilton *et al*. 1997).

Building on these methodological insights, our study considers instruments proposed in the literature for mental health. One commonly used strategy relies on the death of a family member, under the assumption that such an event affects mental health but is not directly related to labour market outcomes (B¨ockerman *et al*. 2022, Burrell *et al*. 2022). However, applying this strategy in the context of employment decisions introduces additional complexity. The exclusion restriction may be violated if the death of a family member influences labour supply through alternative pathways, such as inheritance or changes in household income. For instance, the death of a spouse may compel the individual to continue working for financial reasons, thereby confounding the relationship between mental health and employment.

To address these challenges, we adopt a two-step strategy that strengthens identification. First, we refine our measurement of mental health by regressing alternative indicators of psychological wellbeing on the main mental health variable as a robustness check, helping assess potential measurement bias. Second, we apply an IV approach that uses the death of a close friend as an instrument for mental health, a shock that is plausibly exogenous to labour market outcomes. The discrete-time hazard model is then estimated under alternative distributional assumptions, both with and without unobserved heterogeneity, and incorporates a two-stage residual inclusion (2SRI) procedure to account for endogeneity within the nonlinear framework.(Bound *et al*. 2001, Butler *et al*. 1987, Kessler *et al*. 2002, Zucchelli *et al*. 2007, Disney *et al*. 2006).

The 2SRI method provides an alternative to the conventional IV approach when applied to nonlinear models. In the context of discrete-time hazard analysis, the 2SRI approach has been applied to estimate the effect of a time-varying exposure or treatment on a time-to-event outcome (Garrido *et al*. 2012, Basu and Rathouz 2005). Previous studies have used the 2SRI approach to estimate the effect of various health-related interventions, such as diabetes treatments, drug treatments, and coverage of health services, on hazard outcomes (Ying *et al*. 2019, Mery *et al*. 2016, Tchetgen *et al*. 2015). The 2SRI approach has the advantage of accounting for the endogeneity of the treatment variable, which can improve the accuracy of the estimated treatment effect, but it may still remain biased.

The use of IVs in discrete-time hazard analysis can be challenging due to the need for large sample sizes and the potential for weak instruments. Weak instruments can result in biased estimates and large standard errors, leading to incorrect inference (Terza *et al*. 2008, Angrist *et al*. 1996). In addition, the use of IVs assumes that the exclusion restriction holds, meaning that the IV only affects the outcome through its effect on the endogenous variable, and not through any other pathway. This assumption can be difficult to verify in practice. Studies have highlighted the effectiveness of the IV approach in addressing endogeneity and providing insights into the effects of variables on survival outcomes (Tchetgen *et al*. 2015, Terza *et al*. 2008, Ettner *et al*. 1997).

Our study builds on the econometric framework established by Terza *et al*. (2008) and Terza (2018), which formalises the use of the 2SRI estimator in nonlinear models. In this context, a valid instrument must satisfy two key criteria: (1) it must be strongly correlated with the endogenous explanatory variable (relevance), and (2) it must be conditionally independent of the outcome, given the endogenous regressor and other covariates (exogeneity). Although, these conditions are similar to those in 2SLS, 2SRI differs in how endogeneity is addressed in nonlinear models: by including the first-stage residual as an additional regressor in the second-stage model, rather than using predicted values as in 2SLS.

Literature on the effect of mental health on labour market outcomes in Australia is infrequent and often limited to a sub-sample analysis of males. Cai and Kalb (2007) use HILDA survey to examine the effect of health and labour participation. Using a simultaneous equation model for working-age participants to control for potential endogeneity of health, their findings show that health has a positive effect on retirement. Wilkins (2004) and Brazenor (2002) use cross-sectional data to analyse the effect of 10 different disabilities on labour market outcomes of the older population, such as income level and employment status. Wilkins (2004) shows that, on average, disability reduces the likelihood of labour market participation with different effects for males and females. However, Brazenor (2002) finds that the impact varies depending on the disability type.

Bubonya *et al*. (2019) focus on depressive symptoms as a proxy for having a mental health disorder and its effect on employment status, using the first 14 waves in HILDA. To measure depressive symptoms, they use the same mental health variable available in HILDA as in our paper. As their primary focus is on anxiety and mood disorders, they assign different weights to the five items used to construct the derived mental health variable. Based on this approach, scores below 60 are coded as moderate symptoms, while scores below 52 are considered indicative of severe symptoms.

Methodology

Existing empirical research has adopted two main strategies to address the structural endogeneity inherent in analysing the relationship between health and labour market outcomes. One common approach involves identifying the model through theoretically motivated exclusion restrictions. This requires finding instruments that affect health but not employment. However, the validity of such instruments is often difficult to defend in practice. An alternative strategy relies on exploiting the temporal ordering of events to mitigate reverse causality, typically by modelling the effects of lagged health and employment outcomes (e.g., Steele *et al*. 2013, Olesen *et al*. 2013).

In line with this, recent work by Bubonya *et al*. (2019) using Australian panel data (HILDA) examines the bidirectional relationship between depressive symptoms and employment. They apply linear fixed-effects and dynamic panel models to control for unobserved heterogeneity and to explore feedback mechanisms over time. Their analysis confirms a robust negative effect of poor mental health on employment probabilities, while also documenting that job loss exacerbates psychological distress, reinforcing concerns about simultaneity bias. These insights inform our empirical strategy. We begin by estimating a linear probability model to establish a baseline association between mental health and early retirement. We then proceed to an instrumental variable framework to address potential endogeneity arising from omitted variables and reverse causality. Finally, to capture the timing of retirement decisions in relation to health, we include a discrete-time hazard model.

Baseline Linear Model: LPM and 2SLS

To gain an initial understanding of the relationship between mental health and early retirement decisions, we first estimate a linear probability model (LPM), in which an outcome variable of reported retirement is regressed on lagged mental health and a set of control variables using a pooled regression framework for individuals aged 50–64. This baseline model offers a straight-forward interpretation of the effects. However, this approach does not account for the timing of retirement events, the longitudinal structure of the data, or the possibility of censoring over time. To more appropriately address these dynamic aspects, the analysis is extended using discrete-time hazard models, which explicitly model the retirement decision as a time-to-event process.

The baseline LPM model captures the relationship between mental health and the probability of retirement. The specification is given by:

$$Y_{it} = \alpha_0 + \alpha_1 m_{it-1} + \alpha_2 X_{it} + \epsilon_{it} \quad (1)$$

where Y_{it} is a binary indicator equal to 1 if individual i reports retirement at time t and 0 otherwise, m_{it-1} denotes the lagged mental health score with lower values indicating poorer mental health and higher values reflecting better mental health, and X_{it} is a vector of socio-demographic controls. The error term ϵ_{it} captures unobserved factors affecting retirement. Time subscripts are included; however, we estimate the model by pooling observations across individuals and time, effectively treating the data as if it consists of $i \times t$ independent units.

Although LPM offers a straightforward interpretation, the coefficient α_1 measures the change in the probability of retirement associated with a one-unit change in lagged mental health score, it has several limitations. Notably, the LPM can produce predicted probabilities outside the [0, 1] interval and assumes linearity in probabilities, which might be restrictive given the binary outcome. More importantly, although OLS provides a straightforward estimate, it is likely to suffer from endogeneity due to reverse causality or omitted variable bias, where poor mental health causes and is caused by retirement decisions. For example, retirement could itself impact mental health, creating reverse causality bias.

To mitigate endogeneity concerns, we implement a Two-Stage Least Squares (2SLS) instrumental variables strategy. We use the death of a close friend in the previous period to mental health (t-2) as an instrument for lagged mental health (t-1). This instrument is relevant because bereavement is empirically linked to worsened mental health outcomes (Frijters *et al*. 2010). Under the key assumption that the death of a close friend affects retirement decisions only through its effect on mental health (exclusion restriction), the 2SLS estimates provide a more reliable causal effect of mental health on retirement probability. The first-stage predicts mental health using the instrument, and the second-stage regresses retirement on the predicted mental health and covariates, thus purging the mental health variable of endogeneity bias.

The first-stage of the 2SLS model is specified as:

$$m_{it} = \pi_0 + \pi_1 Z_{it-1} + \pi_2 X_{it} + \eta_{it} \tag{2}$$

where Z_{it-1} is an indicator for the death of a close friend reported at time $t-1$, referring to an event that occurred between $t-2$ and $t-1$. This variable therefore instruments $m_{i,t-1}$ for the outcome observed at time t, capturing the delayed effect of bereavement on mental health.

The additional lag allows for the time it can take for grief to translate into measurable mental health deterioration.

The second-stage uses the lagged predicted mental health score from the first stage, $\hat{m}_{it-1}$, to estimate its causal impact on early retirement:

$$Y_{it} = \beta_0 + \beta_1 \hat{m}_{it-1} + \beta_2 X_{it} + \nu_{it} \tag{3}$$

This IV strategy allows us to recover a local average treatment effect (LATE), interpreted as the causal effect of mental health on retirement among individuals whose mental health was affected by the bereavement shock. A statistically significant and negative $\beta 1$ would indicate that better mental health causally decreases the likelihood of retirement.

To assess instrument strength, we report the first-stage F-statistic. A value above the conventional threshold of 10 suggests a strong instrument. Additionally, validity checks are conducted using alternative specifications of bereavement timing and sub-group analyses by gender.

To account for unobserved individual heterogeneity that may bias the estimates in the baseline linear model, we also estimate a fixed-effects panel regression. This approach controls for time-invariant individual characteristics (e.g., personality traits, early-life conditions) that may jointly influence both mental health and retirement decisions. The fixed-effects specification is given by:

$$Y_{it} = \alpha_1 m_{it-1} + \alpha_2 X_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

where μ_i captures unobserved individual-specific effects, and ε_i denotes the idiosyncratic error term after accounting for μ_i. By differencing out time-invariant unobservables, the fixed-effects estimator helps to address bias from omitted variables that are constant over time. However, it does not account for time-varying endogeneity, which is addressed in instrumental variable strategies.

We include the linear approach alongside the discrete-time hazard analysis to establish a baseline and enable meaningful comparison. Although linear probability models offer a straight-forward starting point for examining the relationship between mental health and early retirement, they come with notable limitations. Chief among these are the assumptions of constant marginal effects and the risk that predicted probabilities may fall outside the valid range of 0 to 1. These constraints become particularly problematic when modelling binary or time-to-event outcomes such as retirement.

Furthermore, linear models are limited in their ability to analyse retirement behaviour, as they do not track individuals over time and therefore fail to fully exploit the longitudinal structure of the HILDA dataset. These models also struggle to capture the timing of retirement decisions and the presence of time-related features such as censoring. To address these limitations, we include a discrete-time hazard modelling framework that explicitly follows individuals over time and accounts for the dynamic nature of retirement behaviour. This nonlinear approach provides a more flexible and accurate representation of the timing of retirement, while appropriately handling duration dependence and potential right-censoring in the data.

Discrete-time Hazard Model

We apply the discrete-time hazard model and assume that individuals become at risk of early retirement at the age of 50 years old, which is in line with the previous literature (Butterworth *et al.* 2006, Melzer *et al.* 2004). Setting the pattern of duration dependence is essential prior to analysing the model, and thus we include an additional 12 age dummies to capture the duration dependence by the age of the individuals, starting from

53 to 64 years old. In our sample of HILDA data, which is based on the number of retirees within each age group, the actual risk of retiring early started when participants are 53 years and older, since the number of reported retirements between the ages 50 and 52 is minimal in our sample.

Our research focuses on understanding how mental health influences the decision to retire. In order to observe individuals who are at risk of retirement, we define a stock sample based on the definition of Jenkins (1995). Over the course of the study, only 45 individuals were present for all 15 waves due to sample attrition, retirement, and death. Our retirement models are estimated on complete sequences of observations, using information up to the wave of first exit if an individual leaves the panel and returns in later waves.

We create additional rows of observation per individual based on the time that this individual was at risk of reporting early retirement in our data. This requires that in general, each respondent, i, contributes T_i rows, where T is the number of time periods i was observed at risk of failure. Jenkins (1995) method enables all periods prior to selection to be ignored. This approach relies on only focusing on the relevant time restricted data for observing the effect of interest. Additionally, the data needs to be rearranged and conditioning on stock sampling prior estimation and need to have an unbalanced data format.

We follow the same notation as Jenkins (1995), so time, t, equals to the initial period, τ , (t = τ) when the individual enters the analysis. Each respondent i contributes s_i years of risks while they are still in employment in the interval between the initial period τ and si, so the time when retirement occurs is ($t = \tau + s_i$). Here, we only rely on the age of an individual reported in the first wave in the survey for evaluating the retirement age. Additionally, we follow the age variables on wave 2 onward. The age and our derived time variable may differ as the timing of the surveys varies between the 18 waves and can cause respondents to report the same age in two consecutive waves, if the timing of the later wave was before their birthday. We assume throughout those individuals aged one year between waves of data.

At the end of the sample, each individual will either have retired early (where δ_i = 1) or will be censored and thus will still be working during the last wave in our sample, (δ_i = 0). The age of the individual $t_i = \tau_i + s_i$ will be the retirement age in a complete duration data or the final age of observation if δ_i = 0. As we ignore all the periods prior to selection into the stock sample (Jenkins 1995), we initially selected only those who are participating in the labour market at their first wave, and therefore drop all individuals who reported their occupational status as retired in the wave when joining the survey.

The dependent variable is a binary indicator for whether the participant remained in or left the labour market through retirement in that wave. We do not allow individuals to report multiple retirements by coming back to the labour market and then leaving again. That is retirement is considered as an absorbing (permanent) state, where individuals cannot return to the labour market.

Consider the discrete-time hazard rate, for individual i, with the conditioned probability of retirement at age t, given by:

$$h_{it} = P[T_i = t | T_i > t; X_{it}, m_{it-1}] \tag{5}$$

Where T_i is a discrete random variable, which represents the last derived age observed in the wave at the end of the sample time period (t = τ + s_i). X_{it} is a vector of socio-demographics covariates based on previous literature, and including marital status, gender, number of individuals in the household, education level, unemployment rate in the local region, and household income, and m_{it-1} is mental health score of individual i at time t-1.

The analysis is conditioned a stock sample, implying that all periods prior to the selection period can be ignored, given that individuals are observed to be in employment at the beginning of the sample time period. The conditional probability of observing the event history of an individual without a complete sequence of responses for the whole sample period is:

$$P(T_i > t | T_i > \tau - 1) = \prod_{t=\tau}^{\tau+s_i} (1 - h_{it}) \tag{6}$$

The conditional probability of observing an individual with a complete sequence between τ and the time of the interview is:

$$P(T_i = t | T_i > \tau - 1) = h_{i\tau+s_i} \prod_{t=\tau}^{\tau+s_i-1} (1 - h_{it}) \tag{7}$$

Equation(7) can be simplified by:

$$(\frac{h_{i\tau+s_i}}{1 - h_{i\tau+s_i}}) \prod_{t=\tau}^{\tau+s_i} (1 - h_{it}) \tag{8}$$

Combining Equation(7) and Equation(8), for the corresponding log-likelihood (with and with-out a complete sequence) for the whole sample yields:

$$logL = \sum_{i=1}^{n} \delta_i log(\frac{h_{i\tau+s_i}}{1 - h_{i\tau+s_i}}) + \sum_{i=1}^{n} \sum_{t=\tau}^{\tau+s_i} log(1 - h_{it}) \tag{9}$$

The log likelihood function in Equation (9) depends on the labour market status of the individual i at the end of the sample time period. The individual can retire before the sample time period, δ_i = 1, or to have a complete duration spell if δ_i = 0.

For individuals who stay in the labour market until the last observed wave, denoted by y_{it} = 0, the value remains the same for all spell periods. On the other hand, for individuals who exit, denoted by y_{it} = 0 for all periods except the exit period, where it becomes y_{it} = 1.

The log-likelihood can be simplified by replacing δ_i with y_{it} in Equation 9:

$$logL = \sum_{i=1}^{n} \sum_{t=\tau}^{\tau+s_i} y_{it} \, log(\frac{h_{it}}{(1-h_{it})}) + \sum_{i=1}^{n} \sum_{t=\tau}^{\tau+s_i} log(1-h_{it}) \tag{10}$$

The hazard rate is the rate of retirement at time t and measures how probable an observation is to retire as a function of age of the individual conditioned on surviving to t-1. The hazard rate is defined by applying a complementary log-log hazard rate, as follows:

$$h_{it} = 1 - exp(-exp(\beta_1 m_{it-1} + \beta_2 X_{it} + \theta_t)) \tag{11}$$

Where θ_t is the discrete-time baseline hazard in our model. We include age dummies for every year at risk of retiring early, starting from 53 to 64 years old, as the actual risk of retiring started at 53 years old. The age dummies between 50 and 52 are not included as they are captured in the model's constant. Therefore, we use the semi-parametric form of our hazard model, where $h_0(t)$ specified as a step function, using dummy variables for each year of age. We also estimate sub-samples of males and females separately as it is likely that the response of labour supply to health shocks differs by gender (Stock and Wise 1988).

Unobserved heterogeneity

Unobserved heterogeneity refers to individual-specific characteristics that are not captured by the observed covariates but still influence the outcome variable, such as differences in preferences, motivation, or unmeasured health conditions (Lemeshow *et al*. 2011). Ignoring these latent factors in a hazard model can lead to biased estimates of the baseline hazard and the coefficients of interest, as the model may attribute part of the variation in hazard time to observed covariates rather than to unobserved differences across individuals. This can result in premature censoring and distortions in the estimated duration dependence, producing either an overestimation or underestimation of the true effect of covariates (Balan and Putter 2019, Heckman and Singer 1984, Lancaster 1990, Nicoletti and Rondinelli 2010).

In general, neglecting unobserved heterogeneity or misspecifying its distribution can bias the estimation of the hazard rate and the coefficients associated with explanatory variables (Heckman and Singer 1984). Individuals with higher unobserved risk may exit the labour market earlier, leading to spurious negative duration dependence (Lancaster 1990). Moreover, when the form of heterogeneity is incorrectly modelled, the estimated relationship between regressors and the hazard rate may not reflect the true behavioural mechanisms (Nicoletti and Rondinelli 2010).

These biases are generally more problematic in duration models than in linear regressions, where the consequences of unobserved heterogeneity are less severe if it is uncorrelated with the regressors. In hazard settings, however, the nonlinearity of the model amplifies the effects of omitted heterogeneity, threatening the validity of the estimates (Nicoletti and Rondinelli 2010, Jenkins 1995, Lancaster 1990).

To assess the sensitivity of our estimates, we also follow Nicoletti and Rondinelli (2010) who use Monte Carlo simulations to evaluate the impact of misspecifying unobserved heterogeneity. Their findings suggest that discrete-time hazard models, particularly those using the complementary log-log specification, are relatively robust to certain forms of misspecification, though accounting for frailty can still improve accuracy.

In our empirical analysis, we begin by estimating a complementary log-log model without frailty, followed by specifications that incorporate unobserved heterogeneity using a gamma-mixture distribution (Jenkins 1997, 1995). Model fit is compared using the Akaike Information Criterion (AIC) to evaluate whether including unobserved heterogeneity meaningfully alters the results. This analysis directly informs the following section, where we extend the framework to include a two-stage residual inclusion (2SRI) approach to address potential endogeneity.

Two-stage Residual Inclusion in Discrete-time Hazard Settings

The methodology used in this study is a 2SRI approach in a discrete-time hazard analysis context. The 2SRI estimator is an alternative to the two-stage least squares (2SLS) estimator but applicable to non-linear settings, while in linear models 2SRI is equivalent to 2SLS. The 2SRI incorporates the endogenous variable in the second-stage in addition to the predicted residual term from the first-stage to further account for endogeneity. The 2SRI estimator relies on previous literature, including the control function approach proposed by Heckman and Robb Jr (1985) and the residual inclusion method introduced by Hausman and Taylor (1981) and Terza *et al*. (2008). The 2SRI has been shown to have desirable properties in a range of empirical contexts (Angrist *et al*. 1996).

In the first-stage, the model is estimated with the instrumental variable as the independent variable and the endogenous variable as the dependent variable. The predicted values of the residuals from this model are then used in the second-stage as an additional covariate to estimate the effect of the exposure variable on the hazard outcome. The 2SRI approach can improve the precision of the estimate and reduce bias due to unobserved confounding, but its validity relies on "strong" instrumental variables and the assumption that the residual from the first-stage is uncorrelated with the unobserved confounders.

We consider a discrete-time hazard model specification mentioned in Equation (10). Hence, the first-stage is further specified as:

$$m_{it} = \alpha_0 + \alpha_1 Z_{it-1} + \alpha_2 X_{it} + u_{it} \tag{12}$$

where u_{it} is a mean zero residual error independent of Z, given X_{it}.

In the first-stage, we regress the endogenous covariates on the exogenous instrumental variable Z, and estimate it using an ordinary least squares model (OLS). We obtain the predicted residuals, $\hat{u}_{it}$, of the endogenous covariates from Equation (12).

We assume that the instrumental variable, death of a close friend (Z), used in Equation (12) is exogenous, meaning it is uncorrelated with the error term in the outcome of the discrete-time hazard model in Equation (12). Additionally, given that the effects of a close friend's death on mental health may not be immediately observable and may take some time to materialise, we account for this potential time lag by including a lagged one-period death of a close friend as an instrumental variable in our analysis.

Moreover, we assume that the instrumental variable used in our approach satisfies the exclusion restriction assumption. This indicates that the instrumental variable (lag of death of a close friend), *Z*, used in the first-stage regression in Equation(12) is only affecting the outcome variable (early retirement) through its effect on the endogenous variable, *m* (mental health score at time t-1), and not through any other unobserved factors. If this assumption is violated, the instrumental variable approach may not be valid and the estimated effect of the endogenous variable, m_{it-1}, on the outcome variable, Y_{it}, may be biased.

We then predict the residuals from the first-stage as:

$$\hat{u}_{it-1} = m_{it-1} - (\hat{\alpha}_0 + \hat{\alpha}_1 Z_{it-2} + \hat{\alpha}_2 X_{it-1}) \tag{13}$$

These residuals, $\hat{u}_{it-1}$, represent the unexplained variation in the endogenous variable, mit–1 after controlling for the exogenous variation provided by the instrumental variable of the death of a close friend at the previous period (Z_{it-2}).

In the second-stage, we estimate the effect of the predicted residuals $\hat{u}_{it-1}$ on the likelihood of early retirement, Y_{it}, using a cloglog hazard model. After following Aalen (1989) and Wan *et al*. (2015) where the covariates are allowed to vary over time, we can show that:

$$logit(P(Y_{it} = 1|\hat{u}_{it-1}, X_{it}, m_{it-1})) = \beta_0 + \beta_1 m_{it-1} + +\beta_2 X_{it} + \beta_3 \hat{u}_{it-1} + v_{it} \tag{14}$$

where $P\,(Y_{it} = 1|\,\hat{u}_{it-1}, X_{it})$ is the probability of $(Y_{it}) = 1$ given the predicted residuals $\hat{u}_{it-1}$ and the vector of socio-demographic covariates, X_{it}. The parameter *β*2 represents the effect of the predicted residuals on logit ($P\,(Y_{it} = 1)$), controlling for Xit and m_{it-1}. v_{it} is a random error term and represents the unobserved factors that affect the outcome variable, Y_{it}. It captures all other factors that might influence Yit but are not included in the model, and it is assumed to be uncorrelated with the instrumental variable, Z_{it-2}, other control variables, X_{it}, and m_{it-1} conditioned on $\hat{u}_{it-1}$.

The discrete-time hazard rate is modelled using a complementary log-log specification, such that:

$$h_{it} = 1 - exp(-exp(\beta_1 m_{it-1} + \beta_2 X_{it} + \beta_3 \hat{u}_{it-1} + \theta_{it})) \tag{15}$$

where $\beta 1$ is the coefficient for mental health status for individual i at time t-1, $\hat{u}_{it-1}$ is the predicated residuals from the first-stage for individual i at time t-1, and other socio-demographic factors for individual i at time t, respectively. θ_{it} is the discrete-time baseline hazard.

We apply the cloglog hazard model that includes a set of exogenous covariates and a discrete-time baseline hazard, θ_{it}, that captures the unobserved factors that affect the hazard of retirement over time. Additionally, we use a semi-parametric approach to model the baseline hazard as a step function, which allows us to estimate the hazard rate at each discrete time t using dummy variables for age to retirement (refer to the next section (section 4) for additional explanation).

Data

This paper uses 18 waves (2001-2018) of the Household, Income and Labour Dynamics in Australia (HILDA)[1] survey. HILDA is a household based panel study which includes information about socioeconomic characteristics, family dynamics and labour market outcomes. The dataset consists of variables related to individuals and household characteristics, including labour market status, wages, and the health status of individuals. Individuals aged 15 and older are eligible for interview. Both personal and self-assessment questionnaires are used in order to obtain information about the participants.

Participants beyond the state retirement age are excluded, as their retirement decisions may not solely be influenced by adverse mental health conditions. During the time of our sample, the Australian government implemented a policy aligning the female state pension age with that of males, resulting in a notable increase in the female retirement age. Our process involves verifying the age of each female participant in relation to the specific wave, excluding those whose age is equal to or greater than the state pension age during that period.

Individuals with missing employment status (i.e. those who refused to respond or did not provide a response) and those with missing mental health scores, the main variable of interest, are excluded from the analysis. In total, 122,808 observations did not report or refused to report their general health status. Furthermore, 63,956 observations are excluded because individuals were above the statutory retirement age for both genders. Finally, 254,468 observations are excluded for being under the age of 50, leaving a total sample of 44,091 observations. When incorporating lagged mental health, we further exclude individuals who reported mental health in only one wave, resulting in a final analytical sample of 32,316 observations.

1 See https://www.melbourneinstitute.com/hilda/

Figure 1. Sample construction and exclusion criteria

Full HILDA sample: 364,427

↓

Exclude respondents outside ages 50–64
254,468 (age < 50), 63,956 (age > 64)

↓

Exclude women reaching pension-eligibility thresholds
1,912

↓

Exclude observations with missing values of their labour market status
4,431

↓

Exclude observations already reported retirement
3,916

↓

Final estimation sample: 32,316

The derived mental health variable in HILDA captures the mental health status of participants as a summary score (1–100), derived from the Short-Form health survey (SF-36) following the method set out in Ware *et al*. (1993). The SF-36 is a self-reported, multidimensional, generic measure of health. Respondents answer 36 short questions regarding their general health status, both physical and mental, relative to other individuals of the same age group, and grade their responses on discrete scales between 1 and 5. The 36 survey items are used to produce an eight-scale profile of functional health and wellbeing as well as a psychometric score. This self-reported questionnaire is based on physical and mental health summary measures, as well as a preference-based health utility index (Ware *et al*. 1993).

The mental health variable derived from the SF-36 consists of five questions. The items invite the respondents to grade their mental health by replying on a discrete scale to how much they agree with the following statements: been a nervous person, felt so down in the dumps nothing could cheer you up, felt down, been a happy person, felt calm and peaceful. The last two items are reverse-coded so that all items correspond to the same qualitative effect. Figure 2 displays the distribution of the derived mental health variable. The distribution shows that mental health scores are heavily concentrated in the higher range, with most participants scoring between roughly 70 and 90. The distribution peaks around the mid-80s, indicating that a large share of respondents report relatively good mental health. The mean score of 74.92 on a 0–100 scale (where 100 represents the best mental health) reflects this overall skew toward higher values.

Figure 2. Distribution of the derived mental health variable in HILDA from the SF-36

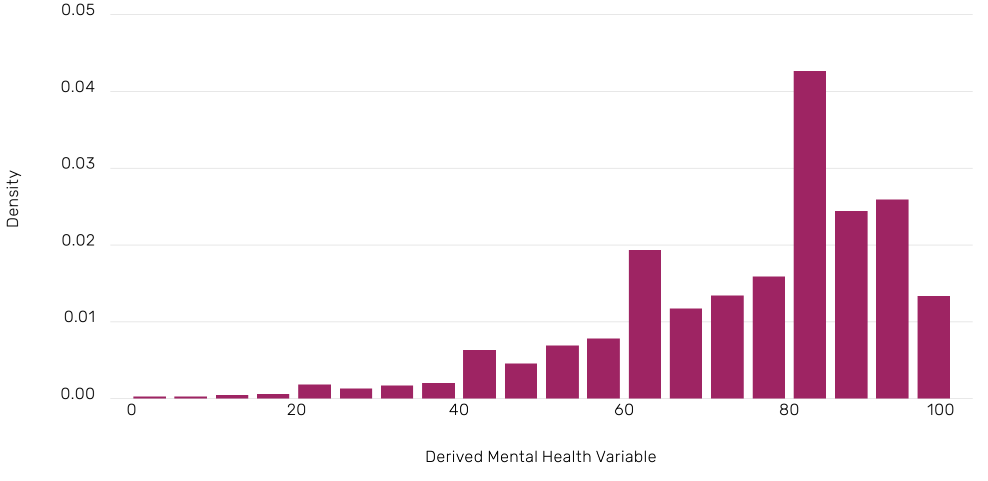


Figure 3 presents the kernel density estimates of the derived mental health scores, stratified by retirement status. The graph reveals a clear distinction in the distribution of mental health between retired and non-retired individuals. Specifically, the density of retired individuals is notably higher at lower mental health scores, indicating poorer mental health within this group. Conversely, the density for non-retired individuals dominates the right tail of the distribution, corresponding to higher (better) mental health scores. This suggests that, on average, retirees report worse general mental health compared to those who remain in the labour force.

Measurement errors in self-reported mental health may occur due to stigma and potential discrimination (Bharadwaj *et al*. 2017, Brohan and Thornicroft 2010, Rüsch *et al*. 2005). While survey-based self-reported questionnaires are commonly used to measure mental health, the potential for inaccuracy due to social desirability bias raises important considerations (Melzer *et al*. 2004). Furthermore, when individuals reported mental health, we expect the information to be influenced by evolving social norms and stigma surrounding mental health disabilities (Bharadwaj *et al*. 2017). However, as societal attitudes towards mental health have evolved in recent years, this shift is reflected in the increased per capita use of public mental health services in Australia (Figure 4).

Figure 3. Density of Mental Health, by Retirement Status

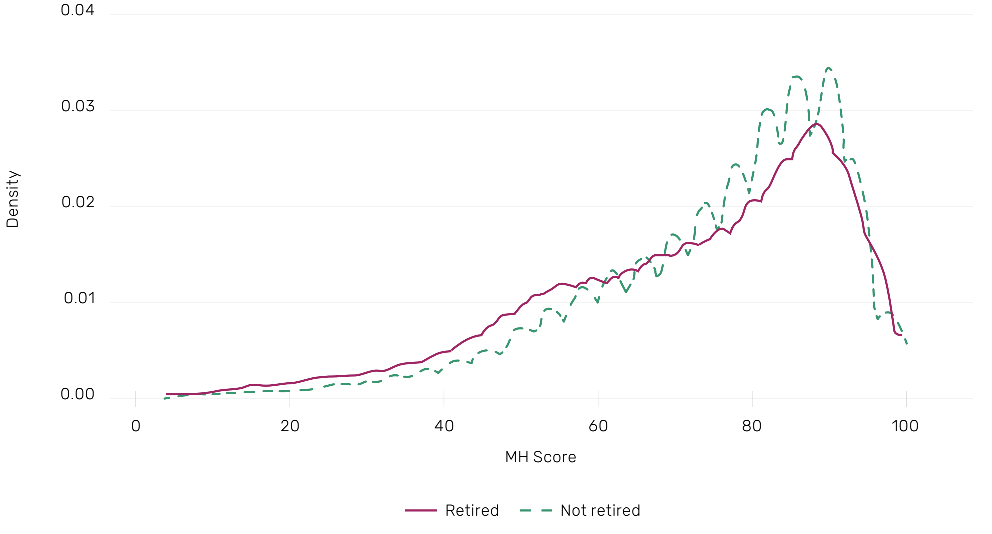
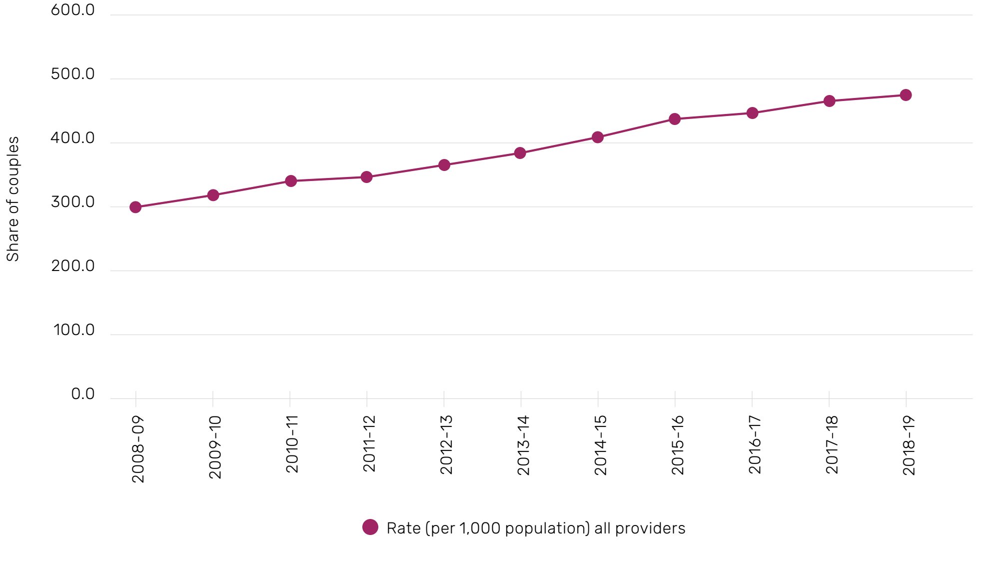


Figure 4. Number of Medicare Subsidised Mental Health Services Consumed by Australians of all providers per year per 1,000 population (Australian Institute of Health and Welfare 2021)



Despite the complex challenge posed by measurement error, we mitigate this concern by analysing the correlation between the Kessler Psychological Distress Scale-10 (K-10) questionnaire (Kessler *et al*. 2002) and our derived mental health variable. The Kessler Psychological Distress Scale includes a 10-item questionnaire, designed specifically for measuring mental health distress caused by anxiety and depressive symptoms following the method of Kessler *et al*. (2002), where higher scores indicate a greater likelihood of experiencing psychological distress. We run a validity check of the self-derived mental health status variable in HILDA, which is available in all 18 waves. However, the measure of Kessler Psychological Distress Scale is not available in every wave and hence cannot be used as the main measurement of mental health in our analysis. The regression method can provide supporting evidence of using the derived mental health variable available in HILDA, while avoiding a potential measurement error by including a more objective in its measurement.

Applying the K-10 as a benchmark, after recoding so that higher values indicate better mental health, we assess the validity of our self-reported mental health variable in the HILDA dataset, thereby enhancing the robustness of our analysis. Our examination reveals a highly statistically significant relationship between the K-10 scores and our derived mental health variable, exhibiting a substantial correlation between the two measures (Table 1). The correlation between these two measure reported to be high with more than 80 per cent. This comprehensive analysis helps alleviate potential concerns of measurement error and underscores the reliability of our findings. By including this approach, we align our investigation with the evolving landscape of attitudes towards mental health and enhance the precision of the derived mental health variable included in our analysis.

Table 1. OLS regression of the derived variable of mental health on K10

VARIABLES	Derived Mental Health
Kessler	2.203*** (0.014)
Constant	108.44*** (0.234)
Observations	13,588
R-squared	0.641
Correlation	-0.801

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

In our paper, an additional regression analysis is applied to examine the association between the derived mental health variable and a binary variable indicating whether individuals have received a formal diagnosis of depression or anxiety by a healthcare professional. This is a formal diagnosis and is more objective and less prone to measurement error. It is important to note that this binary variable is only available in wave 9 and wave 13 and has been queried for a relatively small subset of participants, totalling N=5,436. The regression results, as presented in Table 2, reveal a statistically significant correlation between the binary variable representing a positive diagnosis of either depression or anxiety and the derived mental health score.

Table 2. OLS regression of the derived variable of mental health on depression or anxiety

VARIABLES	Derived Mental Health
Dependanx	-9.470*** (0.326)
Constant	71.96*** (0.244)
Observations	5,436
R-squared	0.134
Correlation	-0.365

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

We include mental health lagged one period to exploit the timing of events between shock to mental health on retirement decisions. This removes bias that would occur if mental health status was measured following the retirement decision during any particular wave. By conditioning on a previous reported mental health status, we can be assured that any health "shock" occurred prior to a retirement decision. Lagged health may also be more informative about the decision to retire than contemporaneous health status, simply because transitions take time. It also may take time for an individual to understand that they suffer from a mental health disorder and to adjust to their new health condition, while observing its effect on labour productivity.

We follow Jones (2009), Zucchelli *et al*. (2007), Disney *et al*. (2006) and include additional covariates to control for other socioeconomics characteristics that might affect early retirement decisions, such as gender, highest educational attainment, and local unemployment rate. Table 3 shows definitions of all the variables included in our analysis. Additionally, we rescaled the household income by the consumer price index in Australia based on 2001 as the base year, in order to capture inflation and ensure values are expressed in constant Australian dollars.

Table 3. Variable Definitions

Variable name	Variable Label	Definition and Measurement
Retired	Reported to be retired	Binary: 1 = retired, 0 = otherwise
Lagged mental health	Lagged self-reported mental health	Continuous scale (0–36), higher = worse mental health
Derived mental health	Mental health status derived from the self-reported GHQ	Continuous GHQ-derived score (0–36), higher = better mental health
Local unemployment rate	Unemployment rate in major statistical region	Continuous percentage (%)
Household size	Number of in-scope persons in household	Count variable
Degree	Holds an academic degree	Binary: 1 = degree, 0 = otherwise
Married	Legally married	Binary: 1 = married, 0 = otherwise
Initial mental health	Initial mental health status	Continuous scale (0–36), baseline measure
Income	Annual income in Australian dollars ($K)	Continuous, measured in thousands of AUD
Death of a friend	Death of a close friend in the last 12 months (instrument)	Binary: 1 = yes, 0 = no
Age	Respondent's age	Continuous, in years
Negative health shock	Negative health shock of physical functioning	Binary: 1 = experienced shock, 0 = no shock
Kessler	Kessler Psychological Distress Scale-10	Continuous scale (10–50), higher = better mental health (rescaled)
Dependanx	Diagnosis of depression and/or anxiety	Binary: 1 = diagnosed, 0 = not diagnosed
D	Early retirement indicator	Binary: 1 = early retired, 0 = censored
T	Analysis time when record ends	Continuous, measured in years
Wave	Survey wave	Integer, indicates survey round

DV: Dummy Variable

An additional measure is incorporated by conditioning mental health on an exogenous indicator of a negative physical health shock. Following Apouey *et al*. (2019), we construct this measure by comparing each individual's expected and actual physical health status across survey waves. Expectations of next period health are derived from a question in the SF-36 survey contained in the HILDA dataset, where respondents indicate their level of agreement (from 1 to 5) with the statement, "I expect my health to get worse." These responses are coded so that higher values reflect a stronger expectation of health deterioration.

Let PH_{it} denote the self-reported physical functioning score for individual *i* at time t, and Eit represent the expected change in health status for the following wave, derived from responses to the statement "I expect my health to get worse." We first compute the change in actual physical health between two consecutive waves as $\Delta PH_{it} = PH_{it} - PH_{i,t-1}$. We then classify this change into three categories:

- −1 if $\Delta PH_{it} < -1$ standard deviation (decline in health)
- 0 if $|\Delta PH_{it}| \leq 1$ standard deviation (no significant change)
- +1 if $\Delta PH_{it} > 1$ standard deviation (improvement in health)

Next, we construct a binary indicator of an unexpected negative health shock, denoted by S_{it}, defined as follows:

$$S_{it} = \begin{cases} 1 & \text{if the individual expected their health to stay the same or improve } (E_{it} \geq 0), \\ & \text{but experienced an actual decline } (\Delta PH_{it} < -1), \\ 0 & \text{otherwise.} \end{cases}$$

In this definition, $S_{it} = 1$ captures cases where the participant's physical health worsened substantially (by at least one standard deviation) despite expecting it to remain stable or improve. Conversely, if an individual anticipated a deterioration in their health and it indeed worsened, Sit = 0, since the change was anticipated. This formulation enables us to isolate unexpected negative health shocks, allowing for a more accurate assessment of how unforeseen declines in physical health influence early retirement decisions.

We also include a discrete-time hazard analysis method that helps us observe the influence of health on the timing of the decision to retire early. To achieve this goal, individuals who are at risk of an early retirement at the start of the HILDA survey are examined. This sample is referred to as a stock sample (Jenkins 1995). We define the stock sample to be comprised of individuals who are aged 50 years or above, have completed a full interview, and are observed to be employed or self-employed in the first wave of the survey. Our main discrete-time hazard analysis sample consists of 9,455 individuals aged between 50 and 64. When additional sociodemographic factors are included, the sample comprises 9,054 individuals, 4,928 males and 4,126 females.

To identify individuals at risk of early retirement in our study, we set an upper age limit of 64, representing the age until which individuals are considered susceptible to early retirement. This choice is consistent with the state retirement age in Australia, which is 65 during the covered period. Individuals aged 64 and below are included in our stock sample, recognising that those over 64 may have different retirement motivations, such as eligibility for social security benefits. Notably, for female participants, we account for variations in the state retirement age until July 2013 when the retirement age was similar for both males and females. This approach determines the observation period for each female participant based on her birth year and the specific state retirement age during the relevant wave.

We follow individuals in every wave until they reach state retirement age or exit the labour market. Individuals cannot be included in all the 18 waves, even if they joined the sample in the first wave of the analysis, since we only estimate the model with workers aged between 50 and 64. Thus, the maximum number of waves per individual is 15. Individuals are followed from the first wave of the survey until they retire, which is assumed to be an absorbing state, are lost to follow-up, or stay in the labour market after state retirement age (65 years old).

We use the death of a close friend as an IV for mental health in both our linear (2SLS) and nonlinear (2SRI) approaches. The relevant question in the HILDA survey asks: "Did any of these happen to you in the past 12 months? Death of a close friend?". We include the IV lagged by one period to align with the lagged structure of our mental health variable. The rationale is that the impact of a close friend's death on an individual's mental health may take time to manifest. Moreover, because the question refers to events in the past 12 months, the death could have occurred at any point within that timeframe, from one month to nearly a year ago, and may already have influenced the previously measured mental health score, depending on the timing of previous wave. By lagging the IV, we aim to allow sufficient time for the event to affect mental health and better capture its causal impact.

Results

Summary Statistics

Table 4 presents summary statistics for the key variables used in the analysis. Approximately 17 per cent of the observations report being retired, indicating a relatively small but meaningful of early retirement in the sample. The average lagged subjective mental health score is around 74.9 (out of 100), with a comparable mean of 74.4 for the initial mental health measure included in the longitudinal analysis, suggesting general stability in reported mental health over time. However, both variables exhibit considerable variation (standard deviation of roughly 17.4), highlighting notable heterogeneity in mental health within the sample.

The average annual income is AU$86,190, with a substantial standard deviation of AU$81,480, indicating a wide dispersion in earnings. Negative health shocks are relatively rare, affecting only 7.5 per cent of the sample, while 13 per cent experienced the death of a close friend, a variable used to capture exogenous emotional distress. Women constitute approximately half the sample (49 per cent), and 62 per cent of individuals are married. About 23 per cent hold a university degree, and the average household size is 2.5 persons. The local unemployment rate, used as a proxy for labour market conditions, averages around 5.3 per cent but ranges from 1.9 per cent to 8.8 per cent, suggesting some regional variation in economic environments.

Table 4. Descriptive Statistics

Variable	Obs	Mean	Std Dev	Min	Max
Retired	44,091	0.169	0.375	0	1
Lagged Mental Health	32,316	74.92	17.42	4	100
Initial Mental Health	38,676	74.41	17.40	0	100
Income	44,091	86.19	81.48	0	1030.59
Negative Health Shock	44,091	0.075	0.26	0	1
Female	44,091	0.49	0.50	0	1
Married	44,091	0.62	0.49	0	1
Degree	41,428	0.23	0.42	0	1
Household size	44,091	2.54	1.23	1	14
Local Unemployment Rate	44,090	5.31	1.11	1.9	8.8
Death of a Close Friend	35,784	0.13	0.34	0	1

DV: Dummy Variable

Table 5 presents descriptive statistics for the variables of interest, disaggregated by individuals' early retirement status and compared with the characteristics of the restricted sample, which includes individuals outside the eligible age range excluded from the main analysis (e.g. pension-aged individuals or younger than 50 years old. On average, individuals report good or very good lagged self-assessed mental health, with a mean of around 75, though this declines among those who have retired early. A notable difference is also observed in the gender composition: approximately 48 per cent of individuals who remain in the labour force are female, compared with around 54 per cent among those who retire early.

Table 5. Descriptive Statistics, by Retirement Status and Restricted Sample

Variable	All	Pre-Retirement	Retirement	Restricted Sample
Retirement Status	0.169	0	1	0.112
Lagged Mental Health	74.924	75.600	71.913	73.859
Academic Degree	0.233	0.248	0.161	0.228
Income	86.193	92.512	55.214	83.441
Female	0.492	0.483	0.538	0.490
Household Size	2.539	2.623	2.127	3.465
Married	0.619	0.619	0.615	0.297
Local Unemployment Rate	5.314	5.309	5.337	5.292
Negative Health Shock	0.075	0.077	0.067	0.087
Death of a Friend (IV)	0.131	0.128	0.143	0.099

Other variables in the analysis show that most individuals in the sample do not have an academic degree. Table 5 also provides a comparison of the information on the local unemployment rate and the number of individuals in the household. The average local unemployment rate is highest for the post-retirement group at around 5.33 per cent, which is slightly similiar to the pre-retirement group (5.31 per cent). The average household size is 2.54 individuals, with 2.62 individuals for the pre-retirement and slightly lower numbers for post-retirement (2.13). This may indicate that individuals tend to have fewer household members after retirement, possibly due to adult children leaving the household or the passing of a spouse.

The restricted sample provides a useful benchmark to assess whether individuals excluded from the core analysis differ systematically from the main study population. Compared with the full sample, the restricted group displays lower average mental health scores and a higher proportion of negative health shocks, suggesting that younger and older excluded individuals may experience different health dynamics. The restricted group also shows lower marriage rates and substantially larger household sizes, reflecting life-cycle differences in living arrangements. These patterns confirm that the main analytical sample is more homogeneous in terms of age-related socioeconomic characteristics, reinforcing the internal validity of the empirical strategy. The individuals included and excluded in the sample share unsystematic characteristics that we expect to not bias the results of the main analysis.

Interestingly, the number of people experiencing negative health shock decreasing post-retirement, suggesting a potential association between an exogenous physical health shock and early retirement. These findings raise intriguing questions about the role of health-related events in influencing retirement decisions and warrant further investigation.

Linear analysis

Table 6 presents the LPM estimates of the effect of lagged mental health on the probability of early retirement. Across all three specifications, lagged mental health is statistically significantly and negatively associated with retirement, suggesting that poorer mental health in the previous wave increases the likelihood of early exiting the labour market. In the most basic model (column 1), which includes only the mental health variable, the coefficient is −0.18 per cent and highly statistically significant at the 1 per cent level. This result is robust to the inclusion of sociodemographic controls (column 2), where the coefficient remains negative and significant, though slightly attenuated to −0.15 per cent. When age dummies are also included to account for nonlinear age-related retirement patterns (column 3), the magnitude of the effect increases slightly to −0.17 per cent, reinforcing the conclusion that deteriorating mental health is a strong predictor of early retirement.

Table 6. Effect of Lagged Mental Health on Retirement (LPM Models)

	(1)	(2)	(3)
Dependent variable:		*Retired*	
Lagged mental health	−0.0018*** (0.0001)	−0.0015*** (0.0001)	−0.0017*** (0.0001)
Sociodemographic controls[a]	–	Y	Y
Age dummies (53–64)	–	–	Y
Observations	32,316	32,057	32,057
R^2	0.0067	0.0495	0.1067

[a]Includes degree, gender, household size, marital status, and regional unemployment rate.
Note: Standard errors in parentheses. ***p < 0.01

Since mental health is likely endogenous, potentially influenced by unobserved factors that also affect retirement decisions, Table 7 presents estimates from instrumental variable (2SLS) models using the death of a close friend in the previous period as an instrument for mental health. In Column 1, where no control variables are included, the effect of lagged mental health on retirement is substantially larger in magnitude, more than six times greater, compared to the corresponding LPM estimate −0.18 per cent, and remains statistically significant at the 1 per cent level. This suggests that the LPM model may fail to adequately capture the causal effect of mental health on retirement, potentially due to omitted variable bias or reverse causality.

Table 7. Effect of Lagged Mental Health on Retirement (2SLS Estimates)

	(1)	(2)	(3)
Dependent variable:		*Retired*	
Lagged mental health	−0.0118*** (0.0032)	−0.0067* (0.0040)	0.0036 (0.0032)
Sociodemographic controls[a]	–	Y	Y
Age dummies (53–64)	–	–	Y
Observations	29,603	29,432	29,432
First-stage F-stat	59.5	33.55	38.8

[a]Includes degree, gender, household size, marital status, and regional unemployment rate.
Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01. All models use L.ledfr as instrument.

When sociodemographic controls are added (column 2), the coefficient decreases to −0.7 per cent and is statistically significant at the 10 per cent level, indicating the robustness of the relationship after adjusting for confounding variables. However, once age dummies are included in column 3, the coefficient becomes minimal and statistically insignificant.

Across all 2SLS models, the first-stage Cragg-Donald F-statistics (ranging from 33.6 to 59.5) exceed the Stock-Yogo critical threshold of 16.38 for the 10 per cent maximal IV size, indicating that the instrument is sufficiently strong and the estimates are not likely to suffer from weak instrument bias. This exceeds the commonly used rule-of-thumb threshold for identifying a strong instrument, with an F-statistic above 10 and hence indicating that 2SLS may capture the causal effect of mental health on retirement.

Together, these findings support the hypothesis that poor mental health also causally increases the probability of early retirement. However, the attenuation and eventual insignificance of the coefficient once richer controls are included, particularly age, highlight the importance of accounting for life-course factors when modelling retirement behaviour. This highlights the need to apply a longitudinal framework to better capture how individuals' retirement decisions evolve over time. In particular, we expect substantial heterogeneity in retirement behaviour across the age distribution, with older individuals likely exhibiting different patterns and sensitivities compared to their younger counterparts.

The fixed-effects estimation results presented in Table 8 show that the coefficient on lagged mental health is negative, consistent in direction with previous models, suggesting that better mental health is associated with a lower probability of retirement. However, unlike earlier findings, this effect is not statistically significant within the fixed-effects framework. This implies that, after accounting for time-invariant individual characteristics, changes in mental health do not have a statistically meaningful impact on the likelihood of retirement within individuals over time. The lack of significance may be due to limited within-individual variation in mental health or retirement status.

Table 8. Effect of Lagged Mental Health on Retirement (Fixed-Effects Model)

Dependent variable:	*Retired*
Lagged mental health	−0.0001 (0.0002)
Income	−0.0002*** (0.00004)
Degree	−0.0757 (0.0408)
Sociodemographic controls[a] Age dummies (53–64)	Y Y
Observations	32,057
Within R^2	0.0688

Note: Robust standard errors clustered at the individual level in parentheses.
***p < 0.01
[a] Includes degree, gender, household size, marital status, and regional unemployment rate.

As shown in Table 9, retirement status remains constant for the majority of the sample across panel waves; only a small proportion of individuals report a change in retirement status, and those who do typically maintain that status over time. This limited within-person variation in retirement partly explains why fixed-effects estimates tend to be less precise or insignificant for retirement outcomes, there is simply insufficient "within" variation to identify the effect reliably.

Table 9. Within-Individual Variation in Retirement Status

Retired Variation	Frequency
0 (No variation)	27,310
1 (Variation)	16,781
Total	44,091

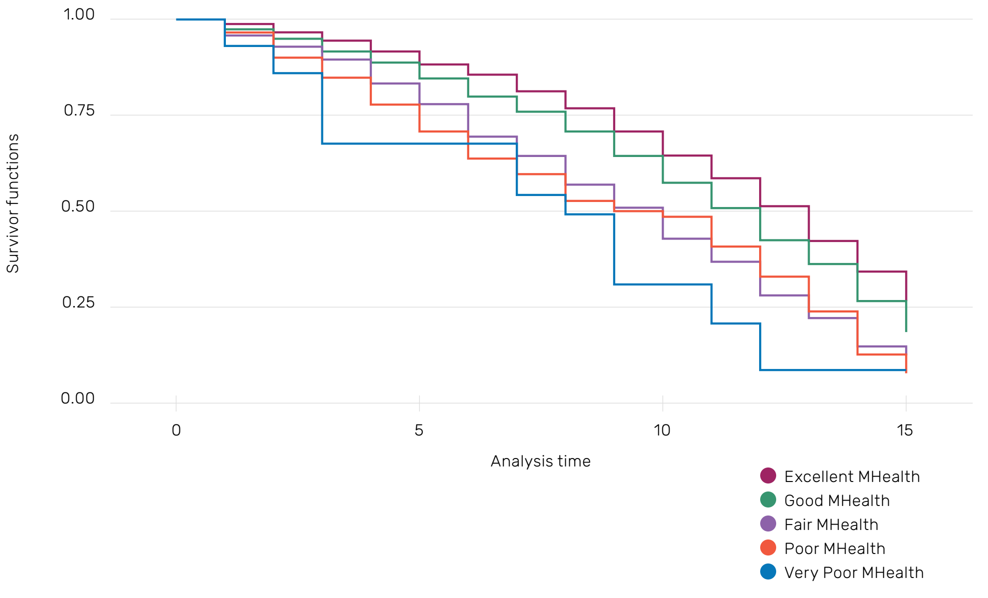
At the same time, other variables such as household income and household size show statistically significant effects, with higher income and larger household size reducing the probability of retirement. This indicates that economic resources and family context remain important predictors of retirement decisions.

Discrete-time hazard model

We apply discrete-time hazard analysis to examine how the results of the baseline model change when tracking individuals longitudinally, wave by wave, until they report early retirement or are excluded from the sample due to attrition or other circumstances. This approach allows us to capture the timing of retirement decisions and better account for dynamic factors influencing exit from the labour market.

Figure 5 presents Kaplan-Meier survival estimates of the probability of remaining in the labour market across successive time intervals leading up to retirement. Mental health is measured at time $t - 1 = t0$ (baseline interview) and treated as a fixed covariate in the survival analysis. The probability of early retirement increases as individuals approach state retirement age. Mental health status is measured at time $t - 1$, representing the most recent observation prior to the retirement outcome, to ensure consistency with the econometric specifications presented in the subsequent tables. Individuals reporting excellent or good mental health at $t - 1$ are more likely to remain in the labour market at time t compared to those with poorer mental health. Conversely, workers who report very poor mental health exhibit the lowest probability of remaining in the labour market relative to individuals who describe their mental health as excellent, good, fair, or poor.

Figure 5. Kaplan–Meier survival estimates, by baseline MH status.



We estimate a series of discrete-time hazard models using a complementary log-log specification to assess how lagged mental health influences the probability of early retirement across waves. Table 10 presents six model specifications with increasing levels of control. In Model (1), we estimate the baseline relationship between lagged mental health and retirement. The results reveal a strong and statistically significant negative association, with a coefficient of −0.0139 ($p < 0.01$). This implies that poorer mental health in the previous wave is associated with a higher hazard of early retirement.

Model (2) introduces a control for initial mental health status, allowing us to net out individuals' initial condition. Both the lagged and baseline mental health variables remain statistically significant, though the magnitude of the lagged effect decreases to −0.09 per cent. This suggests that changes in mental health, rather than static poor levels alone, contribute to early exit from the labour market. Additionally, in Model (3), we add a dummy for experiencing a recent negative health shock. Although the mental health coefficients remain stable and significant, the health shock itself is not statistically significant ($p = 0.178$), implying that acute shocks do not independently predict retirement once mental health is controlled.

Model (4) incorporates household income. The coefficient of lagged mental health remains significant and relatively unchanged −0.086 per cent, while income is also negatively and significantly associated with retirement ($p = 0.017$). This suggests that financial security may partially buffer the impact on retirement decisions. In Model

(5), we further control for sociodemographic characteristics including education, gender, household size, and regional unemployment rate. The effect of lagged mental health remains robust and significant (−0.076 per cent, $p < 0.01$), and household size and having an academic degree are also statistically significant.

Finally, Model (6) adds a full set of age dummies to capture non-linear age-specific retirement risks. The coefficient for lagged mental health remains significant and stable (−0.083 per cent, $p < 0.01$), confirming the robustness of the relationship. Notably, the inclusion of age controls substantially improves model fit and reduces the size and significance of several other covariates. Many age dummies, particularly those in the early 50s, are large and negative with reduction of the effect size for the older age groups, as expected. This pattern aligns with expectations: the negative association between age and early retirement diminishes as individuals approach the statutory retirement age, reflecting prevailing social norms around the timing of retirement.

We also observe a gradient across educational attainment compared to the baseline category of not having any educational qualifications, with higher level of education are positively linked with a decreasing hazard of retiring. Possessing an academic degree, regardless of other variables, exhibits a substantial positive relationship in the probability of retirement. Moreover, the number of individuals in the household has a negative association with the likelihood not to retire early. According to our results, households with a larger number of living individuals would be less likely to leave the labour market earlier than state retirement age, independently of their health difficulties. The results of the full model are reported in Table 16.

Overall, the discrete-time hazard analysis reinforces earlier findings from the LPM and IV models, demonstrating stronger statistical significance and confirming that lagged mental health is a consistent and significant predictor of early retirement. This effect remains robust even after controlling for initial mental health, physical health shocks, income, sociodemographic characteristics, and age-dummies.

Discrete-time hazard model (including unobserved heterogeneity)

In this section, we include a model with unobserved heterogeneity and test the validation of this model compared to a model without frailty. Table 11 presents the results of a gamma-distributed frailty following the method of Jenkins (1997) for observing frailty. The results show that the expected effect of mental health on early retirement decision is -0.014 for the model without frailty and follows the same pattern of the model with frailty. The effect is statistically significant for both models.

Moreover, we estimate the model fit using information criteria (Akaike and Bayesian information criterions) which were greater with the complementary log-log estimator without frailty.

Table 10. Effect of Lagged Mental Health on Early Retirement (discrete-time hazard Models)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	*Early retirement (hazard)*					
Lagged mental health	−0.0139*** (0.0021)	−0.0091*** (0.0029)	−0.0094*** (0.0029)	−0.0086*** (0.0030)	−0.0076*** (0.0029)	−0.0083*** (0.0029)
Observations	29,603		29,432		29,432	
Initial mental health	–	Y	Y	Y	Y	Y
Health shock	–	–	Y	Y	Y	Y
Income	–	–	–	Y	Y	Y
Sociodemographics[a]	–	–	–	–	Y	Y
Age dummies (53–64)	–	–	–	–	–	Y
Observations	9,455	9,139	9,139	9,139	9,054	9,054

[a] Includes: degree, gender, household size, marital status, and regional unemployment rate.
Note: Standard errors in parentheses. ***p < 0.01. Estimated using complementary log-log models.

Table 11. Complementary Log-Log Models of Early Retirement: With and Without Gamma-Distributed Heterogeneity

	No Unobserved Heterogeneity	Unobserved Heterogeneity
Lagged mental health	−0.0139*** (0.0021)	−0.0138*** (0.0036)
Constant	−1.596*** (0.162)	−1.597*** (0.273)
ln(var(ν))	– –	−14.852 (64.841)
Gamma variance	–	3.55×10^{-7}
Observations	9,455	9,455

Note: Standard errors in parentheses. ***p < 0.01. Unobserved Heterogeneity is estimated assuming Gamma frailty.

This shows the similar effect of the independent variable and indicates that our analysis does not set to include frailty. As frailty is not much a concern in this paper and the results do not vary between estimators with or without frailty, we have chosen to apply the complementary log-log regression for the discrete-time hazard analysis assuming no prevalence of frailty in our paper.

Two-stage residual inclusion

To assess the validity of our IV approach, we first estimated the first-stage regression applying LPM, where we regressed mental health score (t-1) on the death of a close friend at time t-2 (Table 17).

The results from the two-stage residual inclusion (2SRI) model presented in Table 12 reinforce the negative and statistically significant impact of lagged mental health on the likelihood of early retirement. Specifically, the coefficient of −1.1 per cent (significant at the 1 per cent level) indicates that a deterioration in mental health in the previous period is associated with a higher hazard of transitioning into early retirement.

Table 12. Two-Stage Residual Inclusion

Two-Stage Residual Inclusion (2SRI)		
Variable	Coefficient	(SE)
Second-stage of 2SRI: Early Retirement		
Lagged mental health	-0.011***	(0.003)
Initial mental health	-0.008***	(0.003)
Income	0.001	(0.001)
Degree	-0.199*	(0.105)
Negative health shock	-0.175	(0.194)
Observations	7,335	
First-stage of 2SRI: OLS Regression on Mental Health Status		
Lagged death of a friend	-1.954***	(0.518)

Note: Standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1
F-statistic (First-stage): 14.18

Initial mental health status, representing time-invariant baseline psychological conditions, also emerges as a significant predictor, with a coefficient of −0.08 per cent (significant at the 1 per cent level). This highlights that both dynamic (lagged) and baseline (initial) mental health exert meaningful influence on retirement decisions. However, income does not appear to have a statistically significant effect on early retirement in this model, with a small positive coefficient (0.001) and a p-value above conventional thresholds. This suggests that after accounting for health, sociodemographics, and age effects, income levels may not directly be associated with early retirement decisions in this sample.

Educational attainment, proxied by holding an academic degree, shows a marginally significant negative effect (−1.99 per cent, p = 0.057), implying that more educated individuals are less likely to retire early, possibly reflecting greater access to less physically or mentally demanding jobs, stronger labour market attachment, or different preferences regarding continued work.

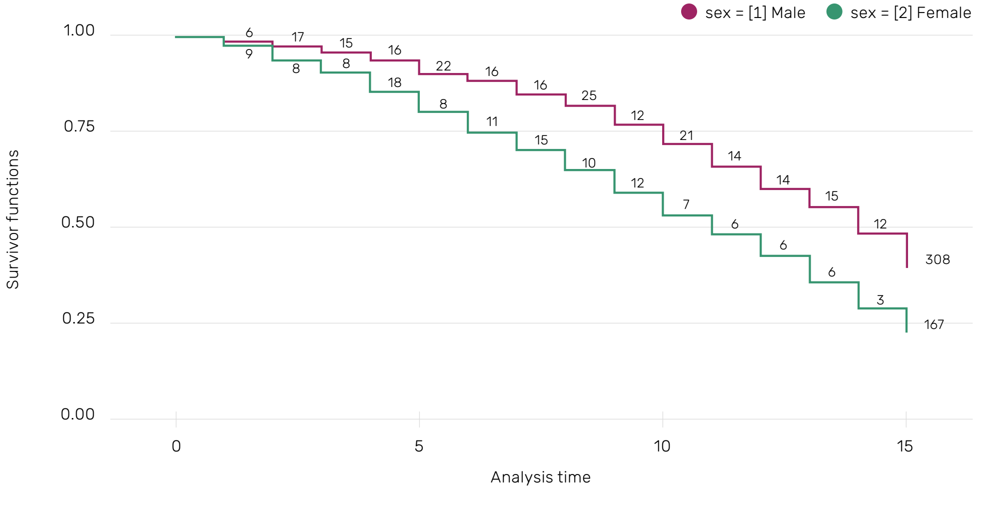
Other sociodemographic controls, such as household size and local unemployment rate, also exhibit significant associations. A larger household size is associated with a smaller risk of early retirement, while higher local unemployment is positively related to retirement risk, potentially capturing economic discouragement effects. Age dummies behave as expected, with older individuals facing higher retirement hazards. The F-statistic for the instrument in the first-stage regression is 14.2, which exceeds the conventional threshold of 10, suggesting that the instrument is not weak.

These findings highlight the critical role of mental health, both dynamic and baseline, in shaping early retirement behaviour and underline the importance of integrating psychological well-being into labour market and retirement policy frameworks.

Sub-sample: Gender-specific

In this section, we present the results of the sub-sample analysis of estimating males and females separately, as previous research traditionally shows that the results differ when estimating the responses for labour market within the different genders. Figure 6 demonstrate the Kaplan-Meier survival estimates by sex. Based on the gender difference alone, independent of other factors, Figure 6 reveals that male workers in our sample exhibit a higher likelihood of remaining in the labour market compared to females. Additionally, mental health may affect males differently compared to females, with different proportions of individuals with a severe or mild mental health disorder in this sub-groups (Australian Bureau of Statistics 2022). The traditional approach when estimating mental health is to observe the effect of mental health on males, however, in this paper we include the results of the two sub-samples (Table 13).

Figure 6. Kaplan-Meier Survival Estimates, by sex



The results in Table 13 present estimates from four different empirical approaches: linear probability models using LPM and 2SLS, and nonlinear discrete-time hazard models using complementary log-log and 2SRI methods across genders. These models aim to evaluate the impact of lagged mental health on early retirement decisions.

Across most models, for both males and females, better lagged mental health is associated with a lower likelihood of early retirement, confirming that mental health issues increase the probability of exiting the labour force prematurely. This effect is consistently negative and statistically significant in nearly all models, except for the 2SLS specification for females, where the sign is positive and statistically insignificant, possibly due to weak instrument bias or sample-specific variation (first-stage F-stats below 10, at 7.907). Notably, the estimated effects tend to be larger in magnitude in the nonlinear models (complementary log-log and 2SRI) for males, particularly after addressing endogeneity in the discrete-time hazard framework.

Comparing across genders reveals notable heterogeneity. The effects of poor mental health on early retirement appear stronger for males than for females in most specifications, underlining the importance of gender-specific analyses when studying retirement behaviour.

Other covariates also exhibit gendered patterns. Education is positively associated with delaying retirement for females, with statistically significant effects across all models. For males, while the direction of the relationship is less consistent and mostly insignificant, the point estimates suggest that having an academic degree may in some cases be linked with earlier retirement, possibly reflecting differences in financial security, job satisfaction, or pension eligibility between educational groups.

Income exhibits consistent effects across linear and nonlinear models and across genders. The association is statistically significant in the linear models for both men and women but not in the nonlinear specifications. This discrepancy may reflect differences in the way time-to-event outcomes are captured or reduced statistical power in the discrete-time hazard models.

Table 13. Comparison of Coefficient Estimates Across Models and Gender

	LPM	2SLS	Cloglog	2SRI
Panel A: Female				
Mental health	−0.0014*** (0.0002)	0.0116 (0.0090)	−0.0057 (0.0041)	−0.0063 (0.0038)
Degree	−0.0307*** (0.0071)	−0.0635*** (0.0210)	−0.3473** (0.1651)	−0.3685** (0.1651)
Income	−0.0006*** (0.0001)	−0.0009*** (0.0002)	−0.0006 (0.0008)	−0.0006 (0.0008)
Negative health shock	−0.0316** (0.0140)	0.0384 (0.0488)	−0.5775* (0.3400)	−0.4792 (0.3403)
Observations	16,192	14,926	4,126	3,320
F-stat first-stage (2SLS)	–	7.907	–	–
Panel B: Male				
Mental health	−0.0022*** (0.0002)	−0.0004 (0.0034)	−0.0147*** (0.0041)	−0.0164*** (0.0038)
Degree	−0.0123* (0.0065)	−0.0185** (0.0073)	0.0174 (0.1380)	−0.0101 (0.1383)
Income	−0.0005*** (0.0001)	−0.0006*** (0.0001)	−0.0010 (0.0008)	−0.0012 (0.0009)
Negative health shock	−0.0078 (0.0125)	0.0069 (0.0214)	−0.0095 (0.2378)	0.0398 (0.2381)
Observations	15,865	14,506	4,928	4,015
F-stat first-stage (2SLS)	–	39.923	–	–

Notes: Each cell reports the coefficient (standard error in parentheses) for the corresponding variable and model.
Significance levels: *p < 0.10, **p < 0.05, ***p < 0.01.

The effect of health shocks is uniformly insignificant across all specifications. This suggests that physical health shocks may have a stronger influence on early retirement among women, possibly due to differing occupational exposures or caregiving responsibilities.

Discussion and conclusion

The present study examines the impact of mental health on labour market participation, specifically the decision to remain in the workforce or retire early. Exiting the labour market before reaching the state pension age can have negative implications, including reduced social interaction and financial insecurity. Policymakers therefore need a clearer understanding of how mental health influences early retirement decisions.

Previous literature has explored the relationship between health and labour market outcomes (Porru *et al*. 2019, Frijters *et al*. 2010, Disney *et al*. 2006, Ettner *et al*. 1997, Hamilton *et al*. 1997), yet the specific role of mental health among older workers remains underexplored. Empirical challenges such as reverse causality, endogeneity, and measurement error further complicate causal inference. To address these, our study applies a range of econometric methods designed to isolate the causal effect of mental health on early retirement.

First, we validate our derived mental health score using alternative subjective measures, in-cluding the Kessler scale (Kessler *et al*. 1999), and medical diagnoses. The high correlation between these measures suggests that our constructed mental health variable provides a reliable representation of individuals' mental health status. Second, we estimate linear probability models, including two-stage least squares (2SLS) regressions using the death of a close friend as an instrument for mental health. This event is assumed to affect labour market participation only through its impact on mental health (Frijters *et al*. 2010).

Although the instrument performs reasonably well, some limitations remain. Only about 13 per cent of respondents reported the death of a close friend, which may restrict variation. Furthermore, the meaning of a "close friend" is subjective and may differ across individuals. Nonetheless, the first-stage F-statistic exceeds 10 for the overall sample, confirming instrument strength. For females, the statistic falls slightly below this threshold at 7.9, but increases to around 40 under the 2SRI specification, reinforcing the validity of our identification strategy.

A further limitation relates to the absence of detailed occupational or industry controls. Job type can plausibly affect physical demands, psychosocial stressors, and exposure to health risks, and may therefore influence both mental health trajectories and early retirement decisions. In our setting, inclusion of occupation may introduce post-treatment bias given that job choice is itself shaped by earlier health and socioeconomic factors. While our models adjust for a broad set of socioeconomic characteristics, including education, income, and household circumstances, that capture some of the systematic differences associated with occupational sorting, we recognise that residual confounding may remain. Future research with richer longitudinal occupational histories would help to further disentangle these channels.

Third, we test for unobserved heterogeneity by estimating discrete-time hazard models both with and without frailty, assuming a gamma mixture distribution (Jenkins 1997, 1995). The results remain consistent across specifications, suggesting that unobserved frailty is not a major concern. Finally, to account for the timing of early retirement, we use discrete-time hazard models that handle right-censoring and exploit the longitudinal structure of the data. These models show a robust and statistically significant relationship between poorer mental health and higher likelihood of early retirement, even after controlling for physical health and socioeconomic characteristics.

Across all specifications, the results consistently show that individuals with better mental health are significantly less likely to retire early. The estimated effects, although modest in size, are economically meaningful. A one-standard-deviation improvement in mental health reduces the probability of early retirement by roughly 2–4 percentage points. However, an immediate deterioration in mental health would require several unit-level changes to produce a large effect on the probability of exiting the labour market prior retirement age.

The gender analysis further reveals that the effect of mental health is stronger and statistically significant for men, while smaller and insignificant for women. This suggests that men's retirement decisions are more sensitive to changes in mental health, possibly reflecting gendered social norms that link male identity more strongly with employment. Women, by contrast, appear more responsive to financial and family-related factors. Lastly, older individuals are more likely to retire early, reflecting both social norms and reduced financial or social penalties for doing so as they approach the state pension age.

The results of our study are broadly consistent with evidence on the effect of general health on labour market outcomes (Disney *et al*. 2006, Bryan *et al*. 2022, García-Gómez *et al*. 2010). However, given the complexity of the relationship between mental health and retirement be-haviour, not all studies reach the same conclusion. For example, Andersen *et al*. (2024) find no causal effect of mental health on early retirement when exploiting a fireworks disaster as an instrumental variable. These contrasting findings highlight the challenges inherent in isolating causal effects in this domain. Our paper contributes meaningfully to the existing literature by providing new evidence on this relationship and by applying a combination of econometric techniques to strengthen identification and robustness.

From a policy perspective, these findings highlight the importance of integrating mental health into retirement and employment policy. Early screening and workplace mental health support can help reduce premature labour market exits. Gender-sensitive interventions, such as promoting open discussions about men's mental health and reducing stigma, could further enhance labour force retention among older workers.

While the estimated effects are relatively modest, they remain economically significant, particularly in the context of cumulative public costs associated with early retirement. Improving access to mental health services and promoting workplace well-being could help delay retirement, thereby extending productive working lives and reducing fiscal pressures linked to ageing populations.

In conclusion, this study contributes new evidence on the causal effect of mental health on early retirement decisions using robust longitudinal and instrumental-variable methods. Our findings underscore that mental health, though not the only driver of early retirement, is a critical factor shaping labour market participation among older workers. Strengthening mental health support, particularly in the workplace, can generate both social and economic benefits.

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A: Full-model: OLS Regression

Table 14. OLS Regression: Effect of Mental Health on Early Retirement

VARIABLES	Retired
Lagged mental health	-0.0017*** (0.0001)
Income	-0.0005*** (0.0001)
Female	0.0360*** (0.0041)
Married	0.0398*** (0.0048)
Degree	-0.0281*** (0.0049)
Household size	-0.0258*** (0.0020)
Local unemployment rate	-0.0080*** (0.0020)
Age 53	-0.1055*** (0.0088)
Age 54	-0.1035*** (0.0089)
Age 55	-0.0914*** (0.0090)
Age 56	-0.0567*** (0.0092)
Age 57	-0.0333*** (0.0093)
Age 58	-0.0184* (0.0094)
Age 59	0.0119 (0.0095)
Age 60	0.0583*** (0.0097)
Age 61	0.1052*** (0.0098)
Age 62	0.1388*** (0.0099)
Age 63	0.1757*** (0.0106)
Age 64	0.2228*** (0.0114)
Constant	0.4176*** (0.0159)
Observations	32,057
R-squared	0.1067

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

B: Full-model: 2SLS Regression

Table 15. 2SLS Regression: Effect of Mental Health on Early Retirement

VARIABLES	Retired
Lagged mental health	0.0036 (0.0032)
Degree	-0.0394*** (0.0073)
Income	-0.0007*** (0.0001)
Household size	-0.0172*** (0.0030)
Married	0.0088 (0.0169)
Local unemployment rate	0.0008 (0.0024)
Age 52	-0.4115*** (0.0167)
Age 53	-0.3960*** (0.0173)
Age 54	-0.3924*** (0.0175)
Age 55	-0.3820*** (0.0162)
Age 56	-0.3422*** (0.0172)
Age 57	-0.3213*** (0.0159)
Age 58	-0.3061*** (0.0151)
Age 59	-0.2735*** (0.0155)
Age 60	-0.2255*** (0.0152)
Age 61	-0.1737*** (0.0152)
Age 62	-0.1354*** (0.0146)
Age 63	-0.1178*** (0.0148)
Age 64	-0.0687*** (0.0157)
Constant	0.3077 (0.2662)
Observations	29,432
R-squared (Centered)	0.0870
R-squared (Uncentered)	0.2659
Root MSE	0.3792
Underidentification test (LM stat.)	38.794
Underidentification p-value	0.0000
Weak identification test (CD F stat.)	38.819

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

C: Full-model: Complementary log-log model

Table 16. Complementary Log-Log Regression: Effect of Mental Health on Early Retirement

VARIABLES	Early Retirement (Hazard)
Lagged mental health	-0.0083*** (0.0028)
Initial mental health	-0.0076*** (0.0029)
Income	0.0006 (0.0005)
Female	0.0620 (0.0836)
Married	0.0613 (0.0989)
Degree	0.5969*** (0.1109)
Professional/Managerial Jobs	-1.9837*** (0.1484)
Negative Health Shock	-0.2812 (0.1941)
Household size	-0.1893*** (0.0544)
Local unemployment rate	-0.0112 (0.0390)
Age 53	-1.5787*** (0.4287)
Age 54	-1.7052*** (0.3763)
Age 55	-1.4337*** (0.2962)
Age 56	-0.4093** (0.1926)
Age 57	-0.6121*** (0.1992)
Age 58	-0.6215*** (0.1981)
Age 59	-0.5594*** (0.1898)
Age 60	-0.3353* (0.1769)
Age 61	-0.0721 (0.1680)
Age 62	-0.1441 (0.1715)
Age 63	-0.1332 (0.1805)
Age 64	-0.0783 (0.1857)
Constant	-0.3713 (0.3381)
Observations	9,054

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

D: Full-model: Second-Stage of 2SRI

Table 17. The second-stage of the Two-Stage Residual Inclusion

VARIABLES	Early Retirement
Lagged mental health	-0.011*** (0.003)
Initial mental health	-0.008*** (0.003)
Income	-0.001 (0.001)
Married	0.117 (0.100)
Degree	-0.199* (0.105)
Negative Health Shock	-0.175 (0.194)
Household size	-0.138** (0.055)
Local unemployment rate	0.149*** (0.041)
Age 53	-1.331*** (0.429)
Age 54	-1.589*** (0.376)
Age 55	-1.471*** (0.296)
Age 56	-0.480** (0.194)
Age 57	-0.732*** (0.201)
Age 58	-0.776*** (0.200)
Age 59	-0.724*** (0.191)
Age 60	-0.505*** (0.177)
Age 61	-0.234 (0.168)
Age 62	-0.304* (0.172)
Age 63	-0.417** (0.181)
Age 64	-0.319* (0.185)
Xuhat	0.052 (0.059)
Constant	-4.847 (4.558)
Observations	7,335

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

E: Full-model: Sub-sample of gender specific

Table 18. OLS estimates of early retirement on mental health and covariates, by gender

VARIABLES	Female	Male
Lagged mental health	-0.001*** (0.001)	-0.002*** (0.001)
Degree	-0.031*** (0.007)	-0.199* (0.105)
Income	-0.001*** (0.001)	-0.001*** (0.001)
Household size	-0.012*** (0.003)	-0.016*** (0.003)
Married	0.067*** (0.007)	-0.023*** (0.007)
Local unemployment rate	-0.012*** (0.003)	-0.007** (0.003)
Negative Health Shock	-0.032** (0.014)	-0.008 (0.013)
Age 53 to 64 Controls	Included	Included
Observations	16,192	15,865
R-squared	0.131	0.152

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19. 2SLS Estimates of Mental Health on Retirement, Instrumented by Death of Close Friend

	Dependent variable: Retired	
VARIABLES	Female (N=14,926)	Male (N=14,506)
Lagged mental health	0.0116 (0.0090)	-0.0004 (0.0034)
Degree	-0.0635** (0.0210)	-0.0185** (0.0073)
Income	-0.0009*** (0.0002)	-0.0006*** (0.0001)
Household size	-0.0040 (0.0082)	-0.0174*** (0.0033)
Married	0.0100 (0.0469)	-0.0241* (0.0140)
Local unemployment rate	-0.0013 (0.0041)	0.0024 (0.0030)
Negative Health Shock	0.0384 (0.0488)	0.0069 (0.0214)
Age 53 to 64 Controls	Included	Included
Constant	480	480
Observations	7,335	7,335
R-squared	335	335

Standard errors in parentheses
*p < 0.05, **p < 0.01, ***p < 0.001, p < 0.10

Table 20. Complementary Log-Log Regression on Retirement by Sex

	Dependent variable: Early retirement (d)	
VARIABLES	Female (N=14,926)	Male (N=14,506)
Lagged mental health	-0.0057 (0.0041)	-0.0147*** (0.0041)
Initial mental health	-0.0068 (0.0042)	-0.0080* (0.0041)
Income	-0.0006 (0.0008)	-0.0010 (0.0008)
Married	0.2223 (0.1428)	-0.1042 (0.1390)
Degree	-0.3473* (0.1651)	0.0174 (0.1380)
Negative health shock	-0.5775* (0.3400)	-0.0095 (0.2378)
Household size	-0.0259 (0.0843)	-0.2362*** (0.0734)
Local unemployment rate	0.0622 (0.0578)	-0.0477 (0.0537)
Age 53	-0.5912	-2.8383**
Age 54	-0.9307*	-2.2630***
Age 55	-0.7205	-1.8665***
Age 56	0.1301	-0.5563**
Age 57	0.2913	-1.1537***
Age 58	-0.0018	-0.8705***
Age 59	0.1140	-0.7936***
Age 60	0.5169	-0.7007***
Age 61	0.7893*	-0.4382**
Age 62	0.7452*	-0.5104**
Age 63	0.4823	-0.2896
Age 64	0.7171*	-0.2862
Constant	-2.2369*** (0.5493)	0.6060 (0.4526)
Number of obs	4,126	4,928
Log likelihood	-1020.27	-1131.84
LR chi2(20)	79.18	136.95
Prob > chi2	0.0000	0.0000

Standard errors in parentheses
*p < 0.05, **p < 0.01, ***p < 0.001, p < 0.10

Table 21. 2SRI Complementary Log-Log Regression on Retirement by Sex

VARIABLES	Female (N=3,320)	Male (N=4,015)
Lagged mental health	-0.0063 (0.0038)	-0.0164*** (0.0038)
Residual from first stage (Xuhat)	0.0072 (0.1205)	0.0688 (0.0670)
Initial mental health	-0.0080** (0.0040)	-0.0094** (0.0038)
Income	-0.0006 (0.0008)	-0.0012 (0.0009)
Married	0.2147 (0.1438)	-0.1149 (0.1395)
Degree	-0.3685** (0.1651)	-0.0101 (0.1383)
Negative health shock	-0.4792 (0.3403)	0.0398 (0.2381)
Household size	0.0090 (0.0857)	-0.2078*** (0.0733)
Local unemployment rate	0.2065*** (0.0603)	0.1027* (0.0558)
Age 53	-0.4963	-2.4146**
Age 54	-1.0005*	-1.9276***
Age 55	-0.9464**	-1.7801***
Age 56	-0.0708	-0.5921**
Age 57	-0.0556	-1.1802***
Age 58	-0.3461	-0.8813***
Age 59	-0.2607	-0.8656***
Age 60	0.1000	-0.7887***
Age 61	0.3809	-0.5138**
Age 62	0.3692	-0.6467***
Age 63	-0.0481	-0.4738**
Age 64	0.1268	-0.4338**
Constant	-2.9029 (9.1336)	0.6060 (0.4526)
Log likelihood	-947.359	-1059.165
Observations	3,320	4,015

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