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Towards Fairer Retirement Outcomes: Health-Related Mortality Modelling

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Abstract

Accurate mortality prediction underpins actuarial practice, informing insurance pricing, retirement income planning, and product design. Building on recent evidence of socio-economic mortality differentials in Australia (Huang, Hui and Villegas, 2025), this study extends that framework by incorporating health-related variables for retirees and distilling them into a transparent Health Index. Using the ABS Personal Level Integrated Data Asset (PLIDA), linked to Medicare and Pharmaceutical Benefits records, we develop interpretable models that integrate the Health Index as an additional factor within the existing socio-economic model. By grouping individuals into risk-based cohorts, the approach mitigates adverse selection risks and preserves equity in risk pooling.

Exploratory analysis shows that mortality risk rises steadily with higher healthcare use, further increased by comorbidity and polypharmacy, but are partly offset by regular preventive care. Notably, pain-medication exposure is associated with an approximately threefold higher observed mortality compared with non-exposed peers, which aligns with the rise in opioid-related deaths over the study window and may reflect addiction. Furthermore, preliminary modelling results demonstrate significant gains in accuracy and fairness, with direct implications for fairer retirement outcomes and improved management of longevity risk. To facilitate adoption, our proposed methodology translates complex models into a concise set of health-related questions potentially suitable for underwriting, bridging actuarial modelling, and health data analytics. This work complements existing socio-economic mortality research, and provides new insights into health-related mortality, offering a foundation for more accurate, transparent, and equitable retirement outcomes in Australia.

1. Introduction

Accurate mortality modelling is fundamental to actuarial practice, underpinning retirement income product design, annuity pricing, and longevity risk management. As Australia's population ages and retirees increasingly rely on superannuation savings to fund longer retirements, understanding differences in mortality outcomes is becoming increasingly important. Traditional mortality models typically rely on demographic factors such as age and gender, which provide a useful baseline but fail to capture the substantial heterogeneity observed across the retiree population. While recent research has demonstrated that socio-economic factors significantly influence mortality outcomes (Huang, Hui and Villegas, 2025), these variables remain indirect proxies for underlying health status. Health conditions, medication usage, and healthcare utilisation provide more direct indicators of mortality risk, particularly at retirement ages where chronic disease prevalence increases, and health trajectories diverge (Christensen K 2009). Incorporating health-related information into mortality modelling therefore presents an opportunity to improve predictive accuracy and support fairer retirement outcomes.

In this study, we extend existing demographic and socio-economic mortality modelling by incorporating health-related variables derived from administrative medical data. Using linked records from the Medicare Benefits Schedule (MBS) and Pharmaceutical Benefits Scheme (PBS) and sourced from the Australian Bureau of Statistics (ABS) Personal Level Integrated Data Asset (PLIDA), we investigate mortality experience across a range of health-based subgroups within the Australian retiree population (Australian Institute of Health and Welfare 2026). These subgroups are defined using indicators of chronic disease, medication exposure, comorbidity, and broader healthcare utilisation, allowing for a more direct assessment of underlying health risk.

As this represents a first major contribution to mortality modelling in the Australian context using health-related variables, the analysis is conducted in three structured stages. First, we undertake a comprehensive exploratory analysis of Medicare-derived variables to understand their individual mortality implications, and their relationships with existing socio-economic factors (2.4 The Socio-Economic Variables and Relationship Between Medical Variables). This includes examining how health indicators vary across income, education, marital status, and socio-economic advantage, as well as identifying potential correlations and interactions between health and demographic characteristics. This step is critical to ensure that the interpretation of medical variables is actuarially meaningful.

Second, informed by these insights, we incorporate the selected Medicare variables into mortality modelling. Health indicators are translated into interpretable risk factors and integrated into mortality calculations, allowing us to quantify the impact of chronic disease, comorbidity, and medication exposure on mortality outcomes (3.3 Medical and Demographic Model). This stage focuses on developing practical and transparent modelling approaches that can be applied within an actuarial framework.

Third, we extend this framework by combining the health-related variables with a recently developed socio-economic mortality model (Huang, Hui, and Villegas 2025), thus producing a unified model that captures demographic, socio-economic, and medical risk factors simultaneously. This integrated approach aims to improve predictive accuracy while maintaining interpretability and practical applicability.

Our analysis highlights several key findings:

- **Health-related mortality differentials:** We observe substantial mortality differences across individuals with varying health profiles. Chronic conditions such as Cardiac Disease and Parkinson’s Disease are associated with elevated mortality risk, while comorbidity and

polypharmacy further amplify this effect. Conversely, indicators such as regular preventative care exhibit more moderate impacts, reflecting the protective role of ongoing medical engagement.
- **Heterogeneity in health-driven life expectancy:** The presence of health conditions leads to meaningful variation in life expectancy across retirees. Individuals with medical conditions experience significantly shorter life expectancy compared to healthier peers, highlighting the importance of incorporating health status into mortality modelling.
- **Implications for retirement income outcomes:** Differences in health-related mortality translate into variation in retirement income outcomes. This suggests that uniform pricing assumptions may inadvertently disadvantage certain groups, while incorporating health information can improve fairness and reduce adverse selection.
- **Implications of transitions:** This study identifies a significant limitation in traditional mortality modelling arising from the assumption of static health status. Health conditions evolve over time, and failing to account for transitions between health states can lead to biased mortality estimates. By incorporating health transitions within a dynamic modelling framework, we demonstrate that progression between medical states materially impacts both life expectancy and retirement income outcomes. The effect of these transitions is analysed in aggregate through changes in life expectancy and annuity pricing, highlighting the importance of dynamic health modelling for more accurate and equitable retirement projections.

By moving beyond static demographic and socio-economic assumptions, the proposed framework provides a more realistic representation of how health evolves over time and influences longevity outcomes.

1.1 Data used

The empirical developments in this study rely on the Person Level Integrated Data Asset (PLIDA), accessed via the ABS DataLab. PLIDA provides a highly secure, granular linkage of cross-agency administrative records, utilising a unique ABS identifier to consolidate information from the Australian Taxation Office, the Department of Education and Training, the Department of Health, the Department of Human Services, and the Department of Social Services.

To construct a comprehensive view of retiree health and mortality, this study integrates several core datasets from within the PLIDA environment:

- 2016 Census Data : Capturing a detailed snapshot of the Australian population's socio-economic status as of Census night (August 9, 2016).
- Social Security Related Information (SSRI) (2009–2016) : Providing longitudinal data on social security benefits, including payment durations, fortnightly payment amounts, marital status trajectories, and highest educational attainment.
- Core Demographics Data (2007–2017) : Capturing vital statistics for individuals aged over 50, including gender, exact year and month of birth, and year and month of death.
- Health Administrative Data : Incorporating records from the Medicare Benefits Schedule (MBS) and the Pharmaceutical Benefits Scheme (PBS), which introduce the critical medical and prescription variables required to extend standard demographic models into health-integrated mortality predictions.

Variables Used for Modelling

Consistent with the socio-economic mortality framework established in Huang, Hui, and Villegas (2025), this study utilises the same set of demographic rating factors, including age, gender, IRSAD deciles, weekly personal income, home ownership status, and marital status. The methodology for extracting and grouping these variables remains unchanged to ensure direct comparability between the demographic-only baseline and the integrated health-related model, with the resultant variables summarised in Table 1.

Table 1: Demographic variable summary.

Demographic Variable	Categories	Actuarial and Clinical Proxy
IRSAD	Deciles 1–10	Community wealth, neighbourhood stability, and local healthcare access.
Weekly Personal Income	<$499, $500–$999, $1000+	Liquid financial capacity to fund care, specialists, and medical payments.
Home ownership Status	Yes, No	Illiquid wealth, baseline financial stability, and long-term housing security.
Marital Status	Married, Single	Social support networks and informal at-home caregiving capacity.
Age	$x \in \{60..110\}$	Baseline mortality risk and broad physiological decline associated with ageing.
Gender	Female, Male	Differences in mortality, morbidity, and disease progression patterns observed across sexes.

The health-based variables and derivation from the MBS and PBS datasets are summarised in Table 2.

Table 2: Medicare variable summary.

Medical Variable	**Derivation Method (MBS / PBS Source)**	**Actual Codes Used (ATC / MBS)**
Diabetes	Mapped from PBS prescription records for blood glucose lowering drugs and insulins and MBS record for Diabetes.	PBS ATC: A10 (Drugs used in Diabetes) diab_mellitus_num
Parkinson's Disease	Mapped from PBS prescription records for dopaminergic agents and other anti-Parkinson drugs.	PBS ATC: N04 (Anti-Parkinson drugs)
Mental Health	Mapped from MBS records for Mental Health	MBS: Mental_Health_num
Antithrombotic Use	Mapped from PBS prescription records for blood thinners and anticoagulant therapies.	PBS ATC: B01AE, B01AF, or B01A (scripts/qty). (Antithrombotic agents)
Pain Medication	Mapped from MBS records of pain medication	MBS: pain_med_num
Cardiac Conditions	Aggregated from PBS cardiovascular prescriptions (e.g., ECGs, echocardiograms).	PBS ATC:any of C07, C08, C09, C02A, C04, C05A, C01A- (_scripts or _qty).
Coronary Bypass	Identified via specific MBS procedural billing codes for coronary bypass.	MBS Items: cor_bypass_num
Lipid Disorders	Mapped from PBS prescription records for cholesterol-lowering medications (e.g., statins).	PBS ATC: C10 (Lipid modifying agents)

1.2 Study Cohort and Exposure Metrics

Drawing from these linked sources, the specific mortality dataset constructed for this study provides national-scale coverage of the Australian population aged 55 and above in the observation window of 2011 to 2016. Across this period, the year-grouped dataset comprises six annual cohorts, encompassing a total exposure of approximately **33.3 million** life-years and **576,176** recorded deaths. Importantly, exposure and death counts remain highly stable across the observation years, ensuring consistency for longitudinal analysis.

The gender-grouped dataset includes three demographic categories with total exposures of **10.4 million**, **11.5 million**, and 0.02 million, corresponding to **285,008**, **290,418**, and 706 deaths, respectively, for the male cohort, female cohort, and a third small cohort corresponding to records with incomplete or unclassified gender information. Due to the lack of information for this third category, we omitted it from this study below.

Due to temporal limitations of the census data, demographic-based analysis was restricted to the final year of the observation window. This yielded a finalised cohort of approximately **4.65 million** total life-years and 115,750 deaths, which comprises roughly 2.5 million female exposures (57,158 deaths) and 2.2 million male exposures (58,592 deaths). The longitudinal depth of the full dataset was preserved for medical analysis and the calibration of transition table parameters, ensuring the model's logic is informed by the total 33 million life-years of observation

2. Exploratory Data Analysis and Key Findings

The integration of Medicare and Pharmaceutical Benefits Scheme records inside PLIDA provides an unprecedented view of retiree health and its impact on retiree mortality. As, to the best of our knowledge, this represents the first attempt to incorporate medical information for mortality prediction within the Australian actuarial context, it is crucial to map the interaction between these newly introduced medical variables and established demographic rating factors. However, translating this administrative data into predictive actuarial features requires careful data engineering.

2.1 Data Architecture and Overcoming Information Leakage

The initial dataset provided a rich summary of Medicare variables, capturing the frequency and volume of healthcare interactions, medical visits, prescription dispenses, and total medicine consumption. This lacked interpretability, and thus was summarised into the disease variables (Table 2). While highly informative, utilising the raw continuous values of these variables introduced a severe risk of information leakage into the mortality modelling. For example, when examining the relationship between observed mortality and the total units of medicine supplied to an individual, initial exploratory data counter-intuitively suggested that lower quantities correlated with higher mortality risk. The most reasonable explanation for this anomaly is exposure time. Individuals who died partway through the observation year inherently had a shorter period to accumulate prescriptions or medical visits compared to those who survived the full year. This structural bias artificially deflated the counts for individuals that died within the year.

The aforementioned information leakage was present in all count-based variables in the dataset, including total medical visits, the number of scripts dispensed under specific PBS codes, and the total quantity supplied for those codes. If these raw values were used for modelling, the model would have learned to predict mortality based on the amount of time an individual was alive during the year, rather than their underlying health risk.

One potential approach to address this information leakage, while retaining numerical granularity, is to use lagged variables (e.g., predicting mortality in year t using continuous medical data from year t−1). This allows the model to utilise the precise volume of the variables. However, due to the limited longitudinal depth in the currently accessible dataset (2011 to 2016), omitting a full year of exposure was impractical as it would result in an unacceptable loss of cohort data. Therefore, we adopted an alternative approach based on transforming the continuous variables into binary indicator variables (e.g., the presence or absence of a specific dispensed medication). This robust simplification allows the model to utilise all available years of data, while mitigating the leakage associated with partial-year exposure. We acknowledge that the inherent trade-off of this approach is the loss of numerical information, as the model cannot currently infer the severity of a condition based on the volume of scripts or units dispensed. Reinstating continuous, lagged variables to capture condition severity will be a primary focus for future iterations of this model once greater longitudinal data becomes accessible.

2.2 Translating Administrative Data to Underwriting Categories

To render the vast dimensionality of the dataset analytically viable and commercially applicable, the granular MBS and PBS variables were aggregated into eight key medical condition categories: Parkinson's Disease, Cardiac conditions, Lipid Disorders, Antithrombotic use, Coronary Bypass, Mental Health, Diabetes, and pain medication exposure (see Table 2 for further details on the derivation). Data sparsity limitations in the current extract prevented the reliable isolation of other severe morbidities, most notably cancer and other terminal illnesses, which remain a priority for future model iterations as additional longitudinal data becomes available.

Crucially, mapping complex administrative codes to recognisable medical conditions bridges the gap between sophisticated data analytics and practical industry application. In a real-world setting, this would directly improve application completion rates and disclosure accuracy, because an applicant is highly likely to reliably answer the underwriting question, "Have you been diagnosed with Parkinson's Disease?", but highly unlikely to accurately answer the specific, "Have you been dispensed any prescriptions classified ATC script code N04?".

2.3 Medical Implications on Mortality

To understand the relationship between health indicators and mortality, we generated comparative mortality curves for individuals with and without specific conditions (Figure 1). By mapping condition-specific survival probabilities with and without the condition over the study window, we can directly observe the medical implications of each condition.

The baseline cohort (comprising individuals who do not show indicators of the relevant conditions) exhibits a standard trajectory, reflecting the natural acceleration of mortality risk associated with aging. Against this baseline, the introduction of chronic morbidity predictably acts as a mortality multiplier. For complex ailments such as Cardiac Disease, Antithrombotic use, and Parkinson's Disease, the survival curves shift upward. This represents the explicit, observable mortality increase due to disease diagnosis/presence, translating a medical diagnosis into a measurable reduction in life expectancy.

At the same time, the empirical data highlights several findings:

- **Effectiveness of medication and preventive care:** The survival curve for individuals flagged with Lipid Disorders demonstrates an exceptionally narrow divergence from the baseline. Rather than signalling a low-risk condition, we believe this instead visualises the efficacy of medical management. Individuals prescribed lipid-regulating medications (such as statins) effectively mitigate their underlying metabolic risk. Furthermore, maintaining these prescriptions requires continuous engagement with primary care networks, facilitating the early detection of other comorbidities. Here, the PBS data thus acts as a proxy for positive health management instead of disease presence. This interpretation is supported by existing literature demonstrating that statin use is associated with reduced all-cause mortality, including a recent systematic review and meta-analysis of propensity score-matched studies that found statin therapy significantly lowers mortality risk (Nowak 2022).

- **The Underdiagnosis Paradox:** Conversely, initial observations suggest an anomalous result where the presence of Diabetes and Mental Health indicators appears to artificially improve mortality outcomes. One possible explanation for this is systemic underdiagnosis (The Lancet Regional Health – Western Pacific 2025). The "Healthy" baseline cohort is inadvertently contaminated by high-risk individuals who suffer from these conditions but lack formal diagnoses or prescription records. Because these unmanaged cases pull the baseline survival curve downward, the observable mortality gap between the diagnosed and undiagnosed populations is artificially compressed, thus masking the true severity of the diseases.
- **The Opioid Signal:** The most striking medical implication revealed in the exploratory analysis is the significant risk associated with prescription pain medication exposure. The impact of taking pain medication on mortality is significant and results in a fivefold increase in mortality. Furthermore, the impact of pain medication on mortality has increased over the years 2011-2016. This aligns with the observation of the Australian Institute of Health and Welfare (Australian Institute of Health and Welfare: 2018), where opioid deaths rose by 62% from 2007 to 2016. Thus, this spike seen with pain medication is likely a spike with opioid-based addiction (Australian Institute of Health and Welfare: 2018).

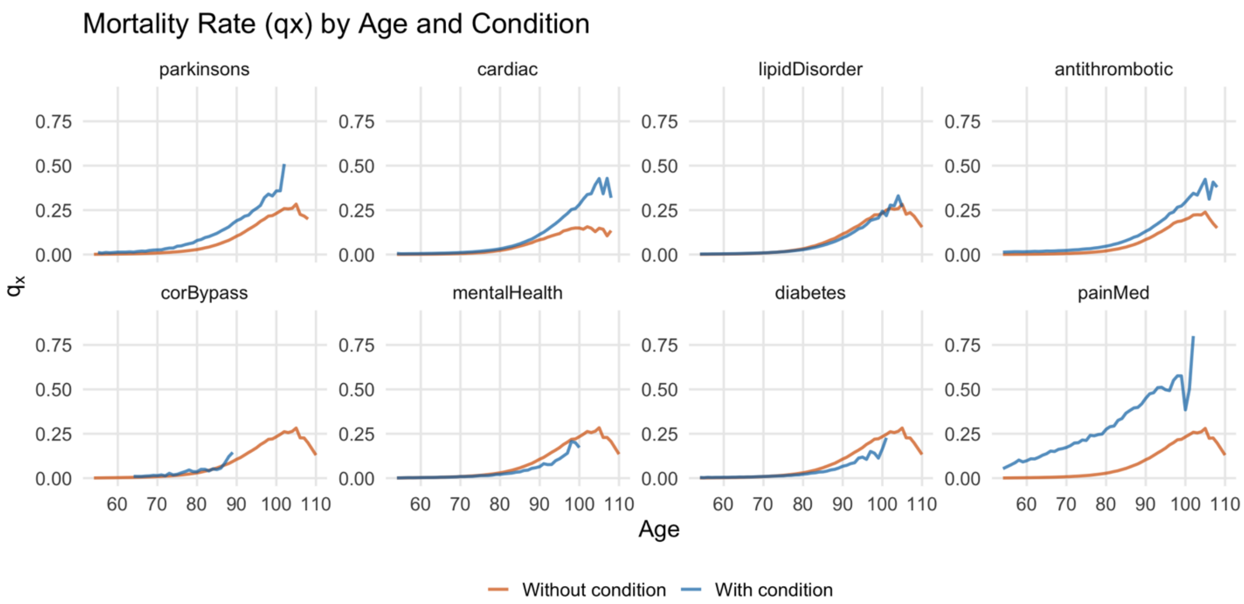


Figure 1: Mortality with and without medical conditions identified using the MBS and PBS datasets.

Lipid disorders have been excluded from further modelling due to a lack of significant mortality differentiation between those with and without the condition. Furthermore, coronary bypass was excluded due to an insufficient volume of observations, lacking the requisite exposure to generate credible actuarial estimates.

2.4 The Socio-Economic Variables and Relationship Between Medical Variables

Intuitively, a person's socio-economic status heavily influences their health and mortality. Clinically, we expect the protective benefits of wealth or education to decline with disease severity (i.e., a wealthy individual and a disadvantaged individual face similar odds when dealing with a late-stage, severe illness). However, because we used binary indicators to denote the simple presence or absence of a condition to prevent information leakage as discussed in 2.1 Data Architecture and Overcoming Information Leakage, then our current dataset cannot measure exact disease severity. Therefore, we analysed the impact of socio-economic factors on health in broad, aggregate terms.

To understand how health interacts with traditional socio-economic rating factors, we mapped the prevalence of seven key condition categories across demographic variables used in Huang, Hui and Villegas (2025), including the Index of Relative Socio-economic Advantage and Disadvantage (IRSAD), personal income, and educational attainment.

IRSAD against medical variables

When considering the interaction between IRSAD and medical conditions (see Figure 2), the aggregate data largely follows a negative relationship, i.e., the more advantaged an individual is, the less likely they are to have the relevant condition. This socio-economic gradient is significantly steeper for metabolic conditions, such as Diabetes, which aligns with the well-documented protective effects of higher health literacy, superior dietary environments, and lifestyle factors associated with affluence (D. Albers, et al. n.d.), (Berkman ND 2011).

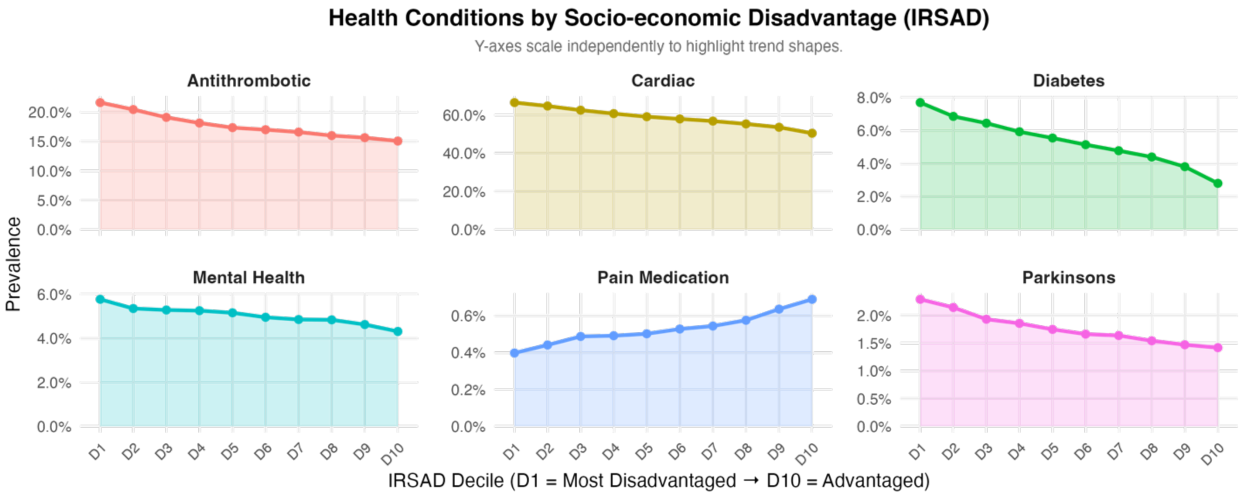


Figure 2: Relationship between Index of Relative Socio-economic Advantage and Disadvantage (IRSAD) and medical conditions.

However, a prominent anomaly emerges when observing pain medication exposure: the relationship completely inverts. The data demonstrates a positive socio-economic gradient, where the most socially advantaged cohorts exhibit a significantly higher prevalence of prescription pain medication compared to the most disadvantaged. This counter-intuitive trend contradicts global literature (H. H. Nestvold 2023), but is corroborated by recent findings from the Australian Institute of Health and Welfare (AIHW) which report elevated rates of illicit drug use (specifically the non-medical consumption of pharmaceuticals) within higher socio-economic demographics (AIHW, 2024). Because the MBS and PBS datasets strictly capture the legal dispensing of these medications, this anomaly is likely flagging a complex intersection of legitimate medical access and affluent pharmaceutical dependency (Australian Institute of Health and Welfare 2024).

One possible explanation for this pattern is that higher-income individuals may have greater access to elective procedures and follow-up care, which could be associated with increased exposure to prescription pain medications. However, this interpretation is speculative and cannot be confirmed using the current dataset. Wealthier retirees bypass public waitlists for major interventions, which structurally require strong post-operative opioids, and can afford the ongoing GP visits to maintain these prescriptions. Conversely, disadvantaged cohorts facing financial barriers often remain unoperated and are forced to manage chronic pain with untracked, over-the-counter (OTC) analgesics. This systemic disparity artificially deflates the observable risk of poorer cohorts in PBS data, potentially reflecting higher rates of prescription pain medication exposure among affluent cohorts.

Marital status against medical variables

When examining marital status (where single includes both widowed and currently unmarried individuals), the data reveals only marginal differences across most medical conditions, suggesting that the baseline physiological deterioration of aging affects both cohorts in a broadly similar manner. However, a significant anomaly emerges within Mental Health indicators, where single retirees exhibit significantly higher disease prevalence than those married. This divergence is likely driven by the inclusion of widowed individuals within the "single" classification, reflecting the psychological toll of grief. Unfortunately, the current dataset lacks the longitudinal depth required to isolate the widowed sub-cohort or identify transitions from the married to the single cohort. Consequently, we cannot definitively pinpoint whether this elevated Mental Health risk stems from recent spousal loss, or the compounding effects of long-term singlehood. Additionally, a consistent trend of lower disease prevalence is observed among the married cohort compared to those classified as single, apart from pain medication exposure where married individuals exhibit higher levels of dependency.

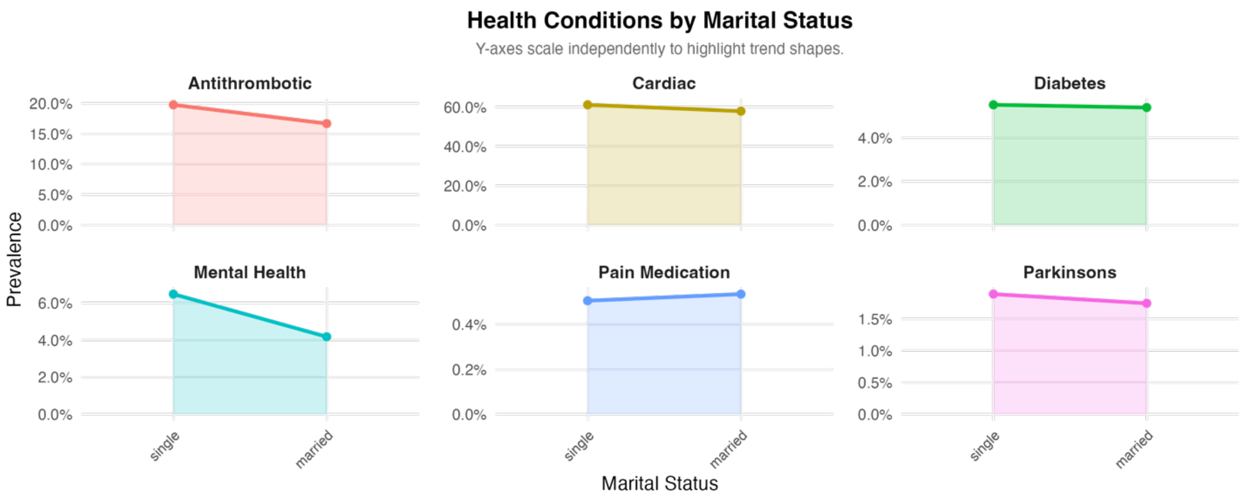


Figure 3: Relationship between the marital status and medical condition prevalence.

Wealth indicators against medical variables

We consider home ownership (Figure 4) and weekly personal income (Figure 5) as proxies for retiree wealth. When evaluating conditions such as Antithrombotic use, Parkinson's Disease, and Cardiac morbidity, the data shows relatively minimal deviation between standard home ownership statuses (owning versus renting), but demonstrates a significantly higher sensitivity to weekly personal income. This pattern may reflect that liquid income is associated with a retiree's capacity to fund ongoing preventative care, maintain high-quality nutrition, and meet continuous medical co-payments; conversely, home ownership is a static, illiquid asset that provides baseline housing security but does not fund daily health interventions.

Home ownership is only reliably observed in the dataset up to approximately age 70, with observations beyond this age displaying considerable noise. Although all ages are presented in the Figure 4, the GLM was fitted by treating home ownership as missing for individuals aged above 67. Therefore, the relationship observed for home ownership in this plot should be interpreted with caution, particularly when extending conclusions to the broader retiree population.

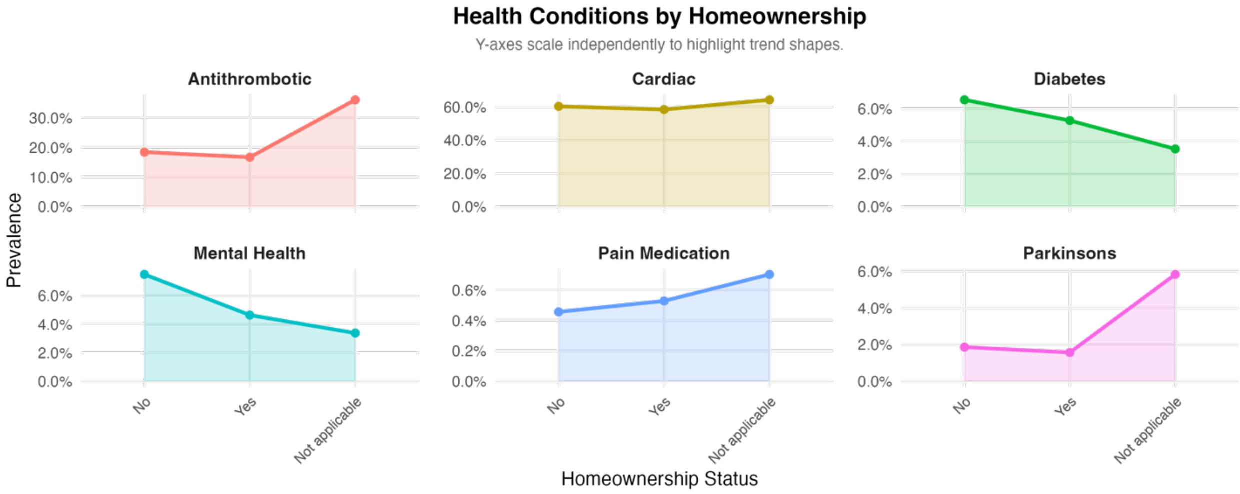


Figure 4: Relationship between the home ownership and medical condition prevalence.

Furthermore, Diabetes and Mental Health exhibit a consistent downward trend against both wealth metrics, suggesting that greater financial stability may be associated with lower prevalence of these conditions. In contrast, pain medication usage diverges, increasing with home ownership while displaying a non-linear, fluctuating pattern against income. This divergence may partly reflect differences in the underlying data structure, as income is measured consistently across the full retiree age range, whereas home ownership estimates are informed by a narrower and noisier subset of observations. Analysis using more granular income bins for medical variables is provided in the appendix.

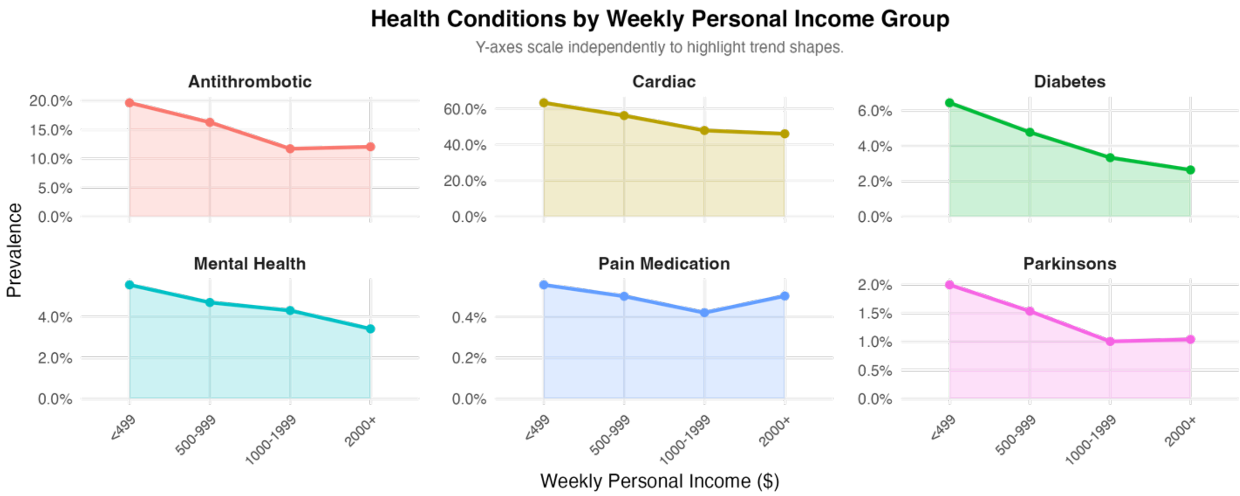


Figure 5: Relationship between the weekly income and medical condition prevalence.

2.5 Key Findings

The above integration and exploratory analysis of the PLIDA demographic data with MBS and PBS administrative health records provides insights into retiree mortality and challenges several traditional actuarial assumptions. We summarise the key findings as follows:

- **The Structural Necessity of Binary Indicators:** Utilising raw, count-based healthcare metrics introduces severe information leakage, as partial-year survival artificially deflates medical utilisation counts. Without greater longitudinal data, converting continuous variables into binary morbidity indicators appears to be a practical approach under current data limitations to ensure the model prices genuine underlying risk rather than exposure-time artifacts.
- **The Underdiagnosis Paradox:** A lack of medical records does not inherently signify good health, but rather potentially frequently flags systemic barriers to care. This is evidenced by uneducated cohorts displaying artificially low Mental Health prevalence, and baseline "Healthy" survival curves being dragged down by unmanaged, undiagnosed Diabetes cases. These findings suggest the possibility of unobserved morbidity that may warrant further investigation.
- **Opioid consumption and socio-economic class:** Prescription pain medication defies standard socio-economic health gradients. While standard morbidities decline as wealth and education increase, pain medication exposure strictly increases among highly educated, home-owning, and high-income cohorts. This may reflect a medically mediated pathway in which more advantaged retirees are more likely to access private elective surgery (AIHW 2008), while procedures such as hip and knee arthroplasty commonly involve short-term postoperative opioid prescribing (Huang P 2022). Exposure to these medications corresponds to a fivefold increase in observed mortality, aligning with national trends in opioid dependency (Australian Institute of Health and Welfare: 2018).
- **The Efficacy of Preventive Management:** Not all positive medical flags serve as mortality multipliers. The negligible mortality divergence observed in cohorts with Lipid Disorders demonstrates the effectiveness of ongoing medical management. Here, PBS data likely acts as a positive proxy for continuous primary care engagement, which effectively neutralises the underlying metabolic risk.
- **Liquid Income vs. Illiquid Assets:** When evaluating wealth, liquid active purchasing power (weekly personal income) serves as a far more sensitive and protective buffer against severe physiological decline (such as Cardiac Disease and Parkinson's Disease) than static, illiquid wealth (home ownership), as it directly funds ongoing preventative care and medical co-payments (Paula Braveman 2014). The effects of liquid and illiquid assets follow a broadly consistent pattern across most medical conditions; however, this relationship reverses for pain medication exposure, where higher liquid assets are associated with reduced prevalence, while illiquid assets are associated with increased prevalence.
- **Potential Bereavement Effect:** The data reveals an anomaly within relationship demographics, where retirees classified as single exhibit a higher prevalence of Mental Health conditions, while other medical conditions appear largely unaffected by marital status. This pattern may reflect the psychological and physiological burden associated with spousal loss (J. Robin Moon 2011). Without longitudinal data distinguishing transitions into widowhood or separating widowed individuals from those who have never married, it is not possible to determine whether this elevated prevalence reflects bereavement effects, long-term singlehood, or other underlying factors.

3. Modelling Framework

To accurately quantify the impact of health and socio-economic variables on retiree longevity, we developed a sequential modelling framework. This approach allows us to isolate the predictive power of traditional demographic variables, evaluate the standalone value of medical administrative data, and finally, combines them into a unified, highly predictive actuarial model.

3.1 Demographic Variable Model

The proposed model utilises a Hermite-spline approach to define the force of mortality (μ_x). This method is based on the previous work done on demographic variables (Huang, Hui and Villegas 2025), and chosen for its ability to capture the age-related convergence of mortality differentials. Statistically, the log force of mortality is expressed as:

$$\text{BaseSpline}(x) = \log \mu_x = ah_{00}(t) + m_0 h_{10}(t) + \omega h_{01}(t) + m_1 h_{11}(t)$$

Where the Hermite basis functions are defined as $h_{00}(t) = (1 + 2t)(1 - t)^2$, h_{10}, $h_{01}(t) = t^2(3 - 2t)$ and $\mathrm{h}_{11}(\mathrm{t}) = \mathrm{t}^2(\mathrm{t}\text{-}1)$. In these equations, t represents the normalised age where the age limits are set at $x_0 = 50$ and $x_1 = 110$.

To this base spline, demographic interactions were incorporated as

$$\log \mu_x = \text{BaseSpline}(x) + h_{00}(t)\left(\sum_j \beta_j D_j\right)$$

Where β_j are the gender specific coefficients, $D_j$and is a vector of demographic variables representing IRSAD decile, home ownership status, marital status, and income level.

3.2 Medical Variables Only Model

A fundamental limitation of many traditional demographic mortality models, including the generalised linear modelling (GLM) framework of Huang, Hui, and Villegas (2025) is the explicit assumption that an individual's risk factors remain static throughout their lifespan. Medical status is inherently dynamic and progressive; therefore, standard static models cannot capture the deterioration of health or the compounding risk of acquiring secondary conditions over time. To overcome this static assumption, the proposed methodology shifts from static demographic evaluation to a dynamic, state-based framework calibrated on the 2011–2016 Medicare Benefits Schedule (MBS) and Pharmaceutical Benefits Scheme (PBS) datasets.

To accurately model this progressive medical decline, we adopted a multi-state Markov chain framework. A primary challenge in integrating administrative medical data is the extreme dimensionality introduced by comorbidity and polypharmacy, which standard regression models struggle to process without severe multicollinearity. To resolve this, the state space of the Markov model was strictly defined by the 14 most common disease combinations and a residue state "other". Based on the observed prevalence of medical conditions during the study period, the model defines the following 15 mutually exclusive health states, which may vary if recalibrated using data from different time periods.

1. Healthy (Healthy)
1. Diabetes only (D)
2. Mental health conditions only (MH)
3. Anti-thrombotic conditions only (A)
4. Cardiac conditions only (C)
5. Cardiac conditions with diabetes (C + D)
6. Cardiac conditions with mental health conditions (C + MH)
7. Cardiac conditions with anti-thrombotic conditions (C + A)
8. Cardiac conditions with anti-thrombotic conditions and diabetes (C + A + D)
9. Cardiac conditions with anti-thrombotic conditions and mental health conditions (C + A + MH)
10. Parkinson's disease (P)
11. Parkinson's disease with cardiac conditions (P + C)
12. Parkinson's disease with cardiac and anti-thrombotic conditions (P + C + A)
13. Pain medication with any condition (P+ with anything)
14. Other conditions (Other)

By clustering individuals into these specific health states, the model explicitly captures the non-linear interactions between diseases within each cluster. This isolates the compounded mortality multiplier of suffering from overlapping conditions (such as the simultaneous presence of Cardiac Disease and Diabetes) rather than treating them as independent, additive risks.

The standard Markov architecture was further structurally modified to better reflect the biological mechanics of aging. In a traditional continuous-time Markov chain, death is treated simply as an absorbing state with its own transition intensity. However, because mortality is driven by demographic factors such as age and gender, treating death merely as a standard state transition fails to reflect these fundamental demographic realities. Instead, we extracted mortality and modelled it as a feature inherent to each specific health state. Under this assumption, and handling competing risks in discrete time, the model thus instead assumes that the risk of death takes precedence and is evaluated prior to any state transitions occurring. This modification allows the framework to calculate a highly granular, age-and-gender-adjusted mortality rate which is uniquely weighted by the individual's current and evolving disease combinations.

The final predictive framework combines this dynamic, state-based medical evaluation with the foundational socio-economic baseline to create a comprehensive mortality pricing architecture. This integrated approach algorithmically accounts for anomalies identified in the exploratory data, such as the "Underdiagnosis Paradox". While this framework provides great analytical benefits for capturing short-term transition intensities and pricing longevity risk based on actual health trajectories, it is important to keep in mind that the empirical calibration remains significantly constrained by the limited longitudinal depth of the 2011–2016 observation window. Chronic diseases unfold over decades, and until richer longitudinal datasets become available, the current modelling results reflect an inability to observe an individual's complete progression from baseline health to complex comorbidity.

An analysis of results based on fitting this model is provided in 4.1 Medical Variables Only Markov Chain Model.

Mathematical overview

"The primary model states are defined by the 14 most prevalent health conditions, accounting for comorbidity, with all remaining conditions aggregated into a cumulative 'other' state (as seen in Figure 7).

Let $X_t \in \{1, ..15\}$ denote an individual's health state at time (t), where each state corresponds to one of the selected medical categories. The model assumes the Markov property, where the future health state depends only on the current state, so

$$\Pr(X_{t+1} = j \mid X_t = i, X_{t-1}, \dots, X_0) = \Pr(X_{t+1} = j \mid X_t = i) = p_{ij}.$$

The health process is then described by a transition matrix

$$\boldsymbol{P} = (p_{ij}),$$

where $(p_{ij})$is the probability of moving from state (i) to state (j) in one time period.

Rather than treating death as just another absorbing state, mortality is modelled separately within each health state. If an individual is in state (i) at age (x) and gender (g), let

$$q_i(x, g)$$

denote the probability of death over the next period. Under the assumption that death is evaluated before any health transition, an individual in state (i) either dies with probability $q_i(x, g)$, or survives and moves to a new health state (j) with probability

$$(1 - q_i(x,g))p_{ij}.$$

This framework therefore separates two components: the progression of medical status through the Markov transition probabilities (p_{ij}), and the mortality risk attached to each current health state through ($q_i(x,g)$).

3.3 Medical and Demographic Model

There are two main approaches to integrate the medical and demographic models: incorporating medical variables into the GLM formed initially using the demographic variables, or alternatively incorporating the GLM into the Markov chain model. The former presents significant structural limitations as inserting highly correlated, high-dimensional medical data into a static GLM inevitably triggers severe multicollinearity issues and fails to capture the dynamic nature of medical status. Therefore, the latter approach was selected as in the developments below.

Prior to selecting this Markov chain framework, a preliminary version of the first approach was implemented to evaluate the statistical significance of medical variables. As seen in Figure 6, while the incorporation of medical variables makes a significant difference in mortality prediction, the inclusion of interaction terms between medical and demographic variables provided negligible improvement

Building on these findings, we then proceed to integrate a demographic GLM inside each distinct state of the Markov chain. Because the model calibrates the demographic coefficients solely on the experience of the cohort with a specific health state, it inherently captures the shifting impact of socio-economic variables across different stages of health. This state-specific calibration allows the framework to organically map the dynamic interactions between wealth and morbidity, entirely bypassing the need for heavily parameterised, explicit interaction terms. Thus, medical conditions are solely used for determining the state and determining transition probabilities for the states, while the GLM introduced in the demographic only model is implemented for all states.

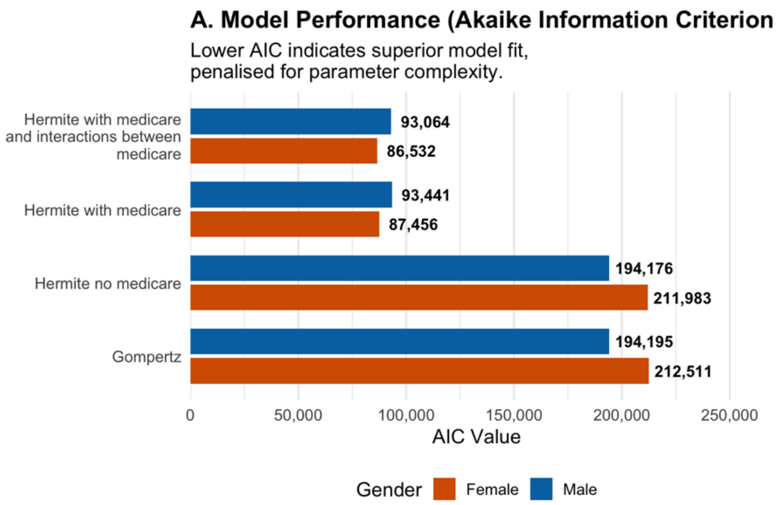


Figure 6: AIC comparison for Gompertz, Hermite spline with only demographic, Hermite spline with demographic and medical variables, and Hermite spline with demographic variables, medical variables and interaction terms between the two.

The initial state space for the Markov chain model (detailed in 2.2 Translating Administrative Data to Underwriting Categories) was constructed using 15 mutually exclusive categories: the 14 most common disease combinations and a 15th residual state (referred to as "other"). However, the demographic data constraints outlined in 1.2 Study Cohort and Exposure Metrics resulted in insufficient exposure across the identified states. This data sparsity necessitated the implementation of an alternative, structurally condensed modelling approach as follows. A hierarchical classification framework was implemented to identify the relevant states. To ensure the health states remained mutually exclusive while preserving sufficient exposure volume, individuals presenting with multiple comorbidities were categorised strictly by their most severe condition. This severity ranking was derived directly from the empirical mortality impacts identified during the Figure 1, establishing a classification hierarchy in descending order of severity: prescription pain medication, Cardiac conditions, Antithrombotic utilisation, Parkinson's Disease, Diabetes, and Mental Health indicators. It is important to acknowledge that a notable limitation of this hierarchical approach 3.3 Medical and Demographic Model is a reduction in transition interpretability compared to a fully specified disease-combination model. A granular state space explicitly tracks the exact onset and resolution of interacting diseases. In contrast, the hierarchical classification acts as a filter, revealing information only about an individual's most acute morbidity. Therefore, an observed transition may be driven by the onset of a more severe ailment, the healing of the dominant condition, or the next most severe preexisting condition surfacing as the primary classification. Because secondary conditions are not tracked simultaneously, the model calculates transition probabilities in aggregation without considering this relevant information, which was implicitly considered in the more granular approach.

Mathematical Overview

To combine medical and demographic information, we let the Markov chain determine the current health state and then apply a demographic mortality model within that state.

In this model, $X_t \in \{1, ..8\}$ denoting health states Antithrombotic, Cardiac, Diabetes, Mental Health, Pain Medication, and Parkinson's, and the baseline healthy state. If $(X_t = i)$, meaning that an individual is in state i at time t then the mortality is modelled using a state-specific GLM of the form

$$\log \mu_i (x, z) = \beta_{i,0} + \beta_i^{\top} z,$$

Where $\mu_i(x, z)$ denotes the mortality rate for someone in health state (i), age (x), and demographic profile (z), and (z) contains the socio-economic variables from the demographic model.

Hence, medical variables determine:

1. the current health state (X_t) and the transition probabilities P, and
2. the transition probabilities (p_{ij}),

while the demographic variables determine mortality within each state through the state-specific GLM.

The model utilises a Hermite-spline approach explained under to define the force of mortality (μ_x). The final selected model is

$$\begin{aligned}\log \mu_{x,s,g,\boldsymbol{D}} = {} & \alpha_{s,g} h_{00}(t) + m_{0,s,g} h_{10}(t) + \omega_{s,g} h_{01}(t) + m_{1,s,g} h_{11}(t) \\ & + \left(\sum_{d \in D} \beta_{IRSAD,s,g} z_d^{IRSAD} + \sum_{h \in H} \beta_{homeowner,h,s,g}\, z_h^{homeownership} + \beta_{married,s,g}\, z_m^{married} \right. \\ & \left. + \sum_{i \in I} \beta_{income,i,s,g}\, z_i^{income} \right) h_{00}(t)\end{aligned}$$

Where the Hermite basis functions are defined as $h_{00}(t) = (1 + 2t)(1 - t)^2$, $h_{10}(t) = t(1 - t)^2$, $h_{01}(t) = t^2(3 - 2t)$ and $h_{11}(t) = t^2(t - 1)$ and D denotes the list of demographic variables, t represents the normalised age $t = (x - x_0)/(x_1 - x_0)$ where the age limits are set at $x_0 = 50$ and $x_1 = 110$. $z_d^{demogvar}$ is an indicator variable that takes value 1 if the individual belongs to demographic category d, and 0 otherwise.

This integrated modelling approach thus combines dynamic medical progression with the demographic mortality structure. The medical component captures how individuals move between health states over time, while the GLM captures how age and socio-economic factors affect mortality conditional on the current state. Put another way, this integrated structure allows the model to capture the shifting impact of socio-economic variables across different stages of health, and to map the dynamic interactions between wealth and morbidity.

On the other hand, the application of this framework faced significant constraints due to insufficient exposure across specific health states. To resolve these limitations and ensure more robust mortality curve estimation, a specialised parameter weighting, and synthesis process was implemented as follows:

Weighted Coefficient Generation: Because certain health states lacked the critical volume of data to independently produce reliable demographic coefficients, the final model parameters were derived through a mechanical weighting mechanism, where the weighting for the state-specific GLM component was calculated proportional to the number of observations within that specific category, utilising a denominator of 25,000.
The final coefficients thus represent a weighted average between these state-specific results, and the robust, population-wide weights established in the demographic-only model by Huang, Hui, and Villegas (2025). By balancing state-specific nuances with population-wide trends, this approach ensures the model remains stable in sparse-data environments while prioritising granular health insights where exposure is sufficient. A primary goal for future iterations, as more longitudinal data becomes available, is to revisit this weighting process to derive mortality estimates solely from the data within each specific cluster, removing the reliance on population-wide averages.

An analysis of the estimated parameters obtained from fitting the above model is provided in 4.2 Medical Variables and Demographic Variable Markov Chain Model.

3.4 Model limitations and challenges

The results of this study are shaped by the practical realities of working with national-level health data. Building this model required balancing clinical depth with the strict memory limits and privacy rules of the secure research environment. The following section outlines the specific challenges and trade-offs made regarding data access, timeframes, and modelling techniques.

<u>Computational and Privacy Constraints</u>

- **ABS DataLab Restrictions:** Due to the highly sensitive nature of the linked national health records, all empirical analysis was strictly confined to the ABS DataLab. This secure enclave imposed rigid constraints on available memory and processing capacity.
- **Memory Limits on Modelling:** Processing the high-dimensional, population-scale dataset within ABS DataLab caused severe memory exhaustion. Consequently, a strong degree of dimensionality reduction was a structural prerequisite to ensure the dataset could be successfully retained, trained, and tested within the DataLab infrastructure.
- **Privacy Controls:** To prevent re-identification, strict ABS privacy protocols mandate a minimum cell count of 10 for both exposure life-years and recorded deaths. This disclosure rule structurally prohibited the modelling of rare disease combinations or niche medical variables with fewer than 100 total observations. Consequently, highly specific comorbidities had to be excluded from the state space, regardless of their theoretical severity or mortality implications

<u>Data Limitations</u>

- **Short Observation Window:** The dataset spans only a six-year window (2011–2016), with a three-year lag built into the training. This "short tail" of data restricts the model's ability to capture long-term effects of medical conditions, delayed impacts of interventions, and limits the robust evaluation of expected lifetimes. This also prevents us from being able to check accuracy of the model on a long tail, thus allowing for transitions and their impacts. In addition to limiting the accuracy of aggregated long-tail measures such as life expectancy, the short observation window also restricts our ability to capture long-term disease progression, analyse transitions that allow for the re-emergence of conditions, and observe the gradual accumulation of comorbidities over time. Consequently, the estimated transition dynamics are more reflective of short-term health movements rather than the full lifecycle evolution of chronic disease.

- **Lack of Diagnosis and Cause of Death Data:** The Medicare (MBS) and Pharmaceutical (PBS) datasets contain doctor visits and prescriptions but lack explicit diagnosis data. Furthermore, the death dataset in PLIDA lacked an ID column, meaning cause-of-death codes could not be linked to individuals.
- **Simplified Dates and Age Approximations:** Due to data size constraints, exact dates of birth and death were reduced to just the year. Consequently, age is only approximate, and the model assumes age changes and deaths occur at the end of the year (or prior to state transitions). .
- **Missing Medical Procedures:** The dataset had missing entries for highly influential procedures like dialysis, chemotherapy, neurosurgery, and radiation oncology, which had to be excluded from the study. We hope to include more severe conditions in our future analysis.
- **Population Coverage:** The dataset only includes retirees aged 55 and above (as of 2011) and excludes individuals not captured by Medicare (such as emigrants or non-residents), potentially introducing survivorship bias.

Methodological Challenges

- **Information Leakage:** Using raw cumulative counts for prescriptions or medical visits introduced severe information leakage, as individuals who died partway through the observation year inherently had less time to accumulate these counts, thus variables were converted to indicator variables as explained in 2.1 Data Architecture and Overcoming Information Leakage.
- **Target Variable Difficulty**: Applying supervised machine learning models (like decision trees or neural networks) was challenging because a clear target variable for predicting mortality was absent prior to defining the clustering mechanism.
- **Simplifying Markov Assumptions:** The Markov Chain model assumes that transitions depend only on the individual's most recent state, ignoring their broader medical history. It also strictly evaluates the presence of a condition rather than disease severity, treating all individuals with a condition as having the same average mortality risk.

Ethical and Industry Safeguards

- **Provider Risk Selection**: A major challenge in implementing highly granular mortality predictions is that insurance or superannuation providers could use individual-level scores to cherry-pick low-risk customers or penalise high-risk ones. To safeguard against this, the model deliberately groups individuals and avoids producing individualised mortality scores.

4. Analysis of Results

4.1 Medical Variables Only Markov Chain Model

As outlined in 3.2 Medical Variables Only Model, the Markov chain model encompassing only medical variables utilises the 14 most common combinations of six primary medical indicators: (1) Prescription Pain Medication Exposure, (2) Cardiac Conditions, (3) Antithrombotic Use, (4) Parkinson’s Disease, (5) Diabetes, and (6) Mental Health. To guarantee mutual exclusivity, the framework incorporates an additional 15th "Other" state to encompass all remaining disease combinations, alongside a prominent "Healthy" baseline state representing the absence of all six conditions.

The dynamic mechanics of the model are driven by annual health shifts. Figure 7 maps the transition probabilities between each of these identified states within a given year, while state-specific mortality distributions are calculates using observations of that state. We summarise the key findings from these results as follows:

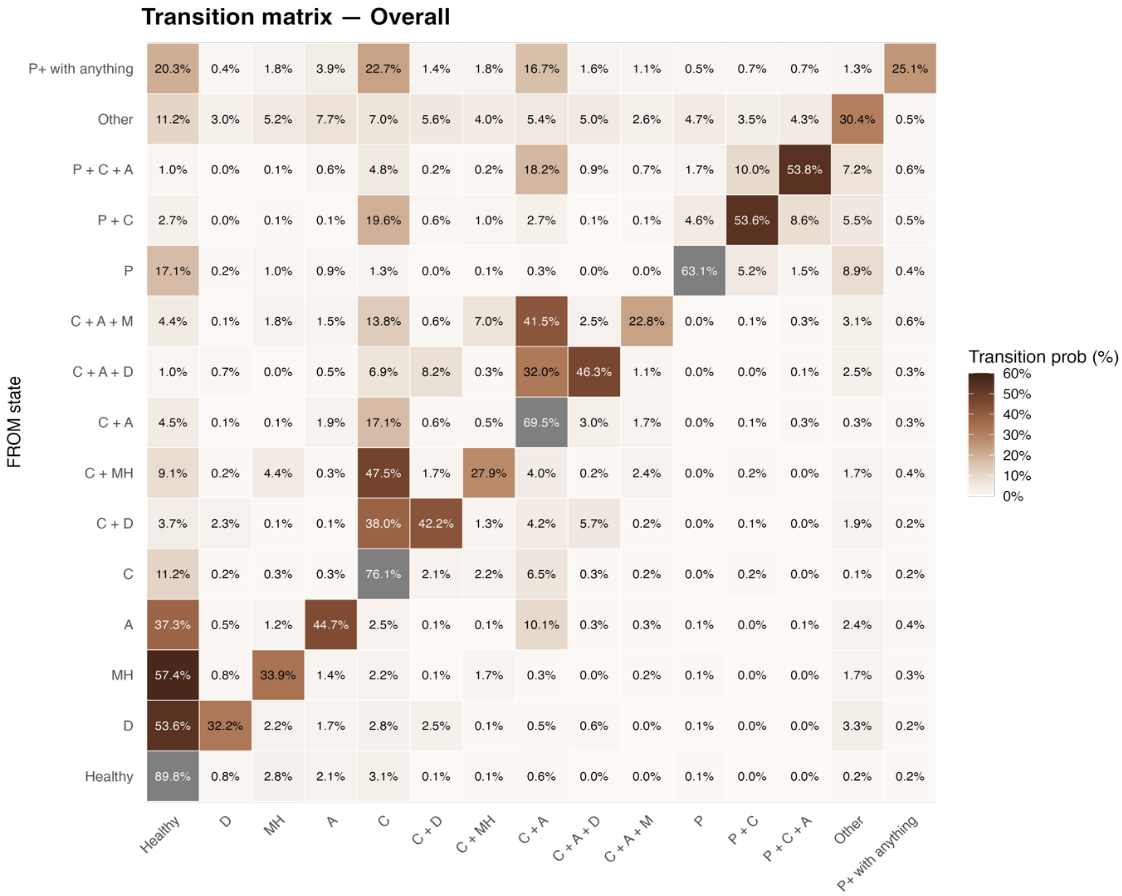


Figure 7: Medical variable only Markov chain model transitions. P: Parkinson's, A: Antithrombotic, C: Cardiac, D: Diabetes, MH: Mental Health conditions and P+anything: Pain medication.

<u>Transition probabilities and state persistence (Figure 7)</u>

- **State Stability:** Transition dynamics vary significantly depending on the complexity of the condition. Healthy individuals exhibit the highest state stability, with an 89.8% probability of remaining in the Healthy state year-over-year. For single chronic conditions, persistence remains relatively high but varies considerably: isolated Cardiac Conditions demonstrate a persistence probability of 76.1%, while Parkinson’s Disease Exposure sits at 63.1%, and Antithrombotic Use at 44.7%.
- **The Resolution Trend** (Mental Health and Diabetes Exceptions): Mental Health (MH) and Diabetes represent notable deviations from the trend of persistent illness, as individuals are significantly more likely to transition out of these isolated states than remain in them. The probability of an individual reverting from an isolated MH condition to a baseline Healthy state is 57.4%, compared to only a 33.9% probability of persisting in the MH state. Similarly, individuals with isolated Diabetes have a 53.6% chance of reverting to Healthy, versus a 32.2% chance of remaining in the diabetic state. This high probability of resolution can also be observed in states with comorbidity, where the presence of these specific conditions will frequently result in individuals shedding the MH or Diabetes component and reverting to their primary baseline disease, rather than persisting in the complex, multi-morbid state. For example, individuals with combined Cardiac and MH conditions are

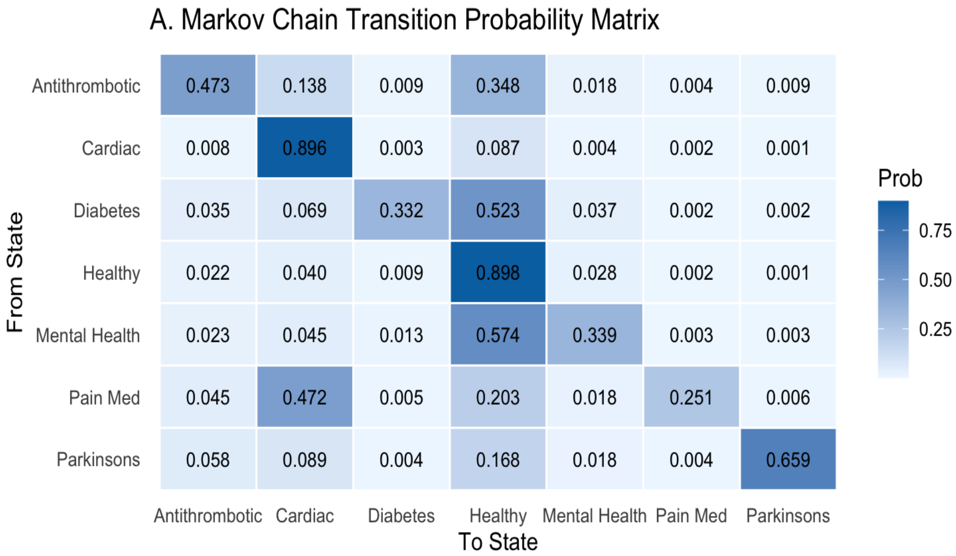
significantly more likely to revert to an isolated Cardiac state (**47.5%**) than to remain in the combined co-morbid state (**27.9%**).

Impact of age and gender on transitions

- **Age as a Primary Driver** (Table 9: Difference in transition probabilities between age bins 50-70, 70-90, and 90+. Each plot denotes the difference between older to younger bins.)**:** Age significantly governs transition dynamics. As individuals progress from the 50–70 age cohort to the 70–90 and 90+ brackets, the probability of reverting to a Healthy state experiences a precipitous decline. By age 90+, reverting to a Healthy baseline is exceedingly rare, and the transition dynamics are overwhelmingly dominated by disease persistence and the accumulation of co-morbidities.
- **Insignificance of Gender** (Table 8)**:** When controlling for the initial baseline health state, gender demonstrates no statistically significant impact on transition trajectories. As such, age-binned transitions were retained in the final model architecture, while gender-based transition splits were omitted. Nevertheless, the gender-based transitions suggest a consistently higher probability of female recovery within a year, as well as a correspondingly higher rate of male disease persistence. Although excluded from the final dynamic model, the independent gender matrices revealed that across every evaluated condition, females were markedly more likely to revert to a baseline Healthy state.

4.2 Medical Variables and Demographic Variable Markov Chain Model

The integrated demographic GLMs within a multi-state Markov chain architecture allows an organic mapping of the dynamic interactions between wealth, status, and morbidity, without the need for heavily parameterised interaction terms. We now summarise the key findings from this model fit (see 3.3 Medical and Demographic Model).



From State \ To State	Antithrombotic	Cardiac	Diabetes	Healthy	Mental Health	Pain Med	Parkinsons
Antithrombotic	0.473	0.138	0.009	0.348	0.018	0.004	0.009
Cardiac	0.008	0.896	0.003	0.087	0.004	0.002	0.001
Diabetes	0.035	0.069	0.332	0.523	0.037	0.002	0.002
Healthy	0.022	0.040	0.009	0.898	0.028	0.002	0.001
Mental Health	0.023	0.045	0.013	0.574	0.339	0.003	0.003
Pain Med	0.045	0.472	0.005	0.203	0.018	0.251	0.006
Parkinsons	0.058	0.089	0.004	0.168	0.018	0.004	0.659

Figure 8: Hierarchical medical state definition Markov chain model transitions.

Hierarchical State Classification and Transitions

To resolve data sparsity issues while maintaining mutual exclusivity, the integrated model utilises a hierarchical classification system based on the most acute morbidity observed. Figure 8 presents the estimated transition matrix illustrating the annual probability of moving between these primary health states.

- **State Persistence and Stability:** Transition dynamics vary by condition complexity. The Healthy state exhibits the highest year-over-year stability at 0.898, closely followed by Cardiac at 0.896. This suggests that once these chronic conditions are identified, individuals remain in these states with high probability.
- **The Recovery Trend**: In contrast, Mental Health (MH) and Diabetes exhibit lower persistence. There is a 0.574 probability of reverting from isolated MH to a Healthy state, and a 0.523 probability for Diabetes. These resolutions are often driven by individuals "shedding" secondary medical flags or reverting to their primary baseline condition.
- **Avenues of Transition:** Intermediate states like Antithrombotic (0.473) and Pain Medication (0.251) show lower persistence, reflecting their usage for transient medical episodes. However, for the pain medication cluster, there was no observed interaction between pain medication usage and any other medical indicator in the MBS/PBS dataset. This lack of comorbidity reinforces the implication of medically induced opioid addiction, which is likely captured by the proportion of individuals who remain in that state long-term. Conversely, those who transition out of the state likely utilised the medication for temporary post-operative recovery or short-term trauma.

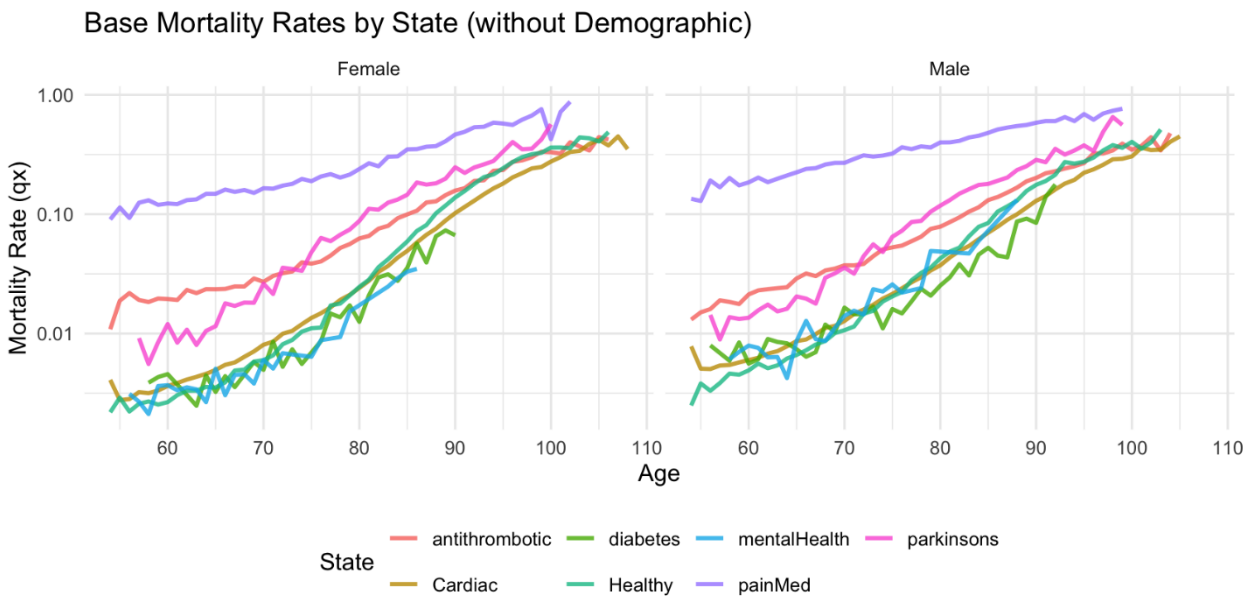


Figure 9: Mortality curves for hierarchical medical variable-based clusters.

<u>State-Specific Mortality Trajectories</u>

By nesting demographic GLMs within these states, the model captures the shifting impact of socio-economic variables across different stages of health. The base mortality rates (q_x) for each health cluster are modelled prior to individual socio-economic weighting (Figure 8).

- **The Opioid Mortality Spike:** The pain Medication cluster exhibits the most striking mortality trajectory, with a roughly fivefold increase in observed risk compared to Healthy peers. This aligns with national data regarding the rise in opioid-related deaths and underscores the risk associated with pharmaceutical dependency in affluent cohorts.
- **Biological Convergence:** While mortality differentials between states like Healthy and Diabetes are pronounced in early retirement, these curves begin to converge at advanced ages (90+). This pattern is consistent with the hypothesis that biological aging becomes increasingly important at advanced ages.

- **Antithrombotic significance:** As shown Figure 9, the Antithrombotic state exhibits relatively high mortality rates across ages and a high probability of remaining in the same (Figure 8), potentially suggesting a persistent underlying cardiovascular condition. Although Pain Medication exhibits the highest mortality, it is comparatively transient, with only around a 25% probability of remaining in the same state. In contrast, the Antithrombotic state has a substantially higher persistence, with approximately a 47% probability of remaining in the same state and a further 13% probability of transitioning into Cardiac conditions. As a result, individuals in the Antithrombotic state are more likely to remain in elevated-risk conditions over time. When these transition dynamics are incorporated into the Markov framework, the cumulative exposure to higher-risk states leads to a lower predicted life expectancy and corresponding deviations in annuity payments.

4.3 State Specific Demographic GLM

This is an overview of the GLM model used within the state-based Markov model details in 4.2 Medical Variables and Demographic Variable Markov Chain Model. The resultant coefficients for each gender-state combination is provided in Figure 10 and Figure 11.

Finalised Weighted GLM Coefficients - Male

Weighted proportional to observations (n/25,000)

Health State	alpha	m0	omega	m1	IRSAD 1	IRSAD 2	IRSAD 3	IRSAD 4	IRSAD 5	IRSAD 6	IRSAD 7	IRSAD 8	IRSAD 9	Home-owner	Married	Inc $500-999	Inc $1000+
healthy	−1.78	−16.22	−0.82	−3.77	−0.03	−0.18	−0.45	−0.54	−0.58	−0.66	−0.69	−0.75	−0.90	−2.29	−0.78	−0.69	−1.19
painmed	−1.91	−8.85	0.01	0.03	0.12	0.02	−0.22	−0.13	−0.12	−0.22	−0.18	−0.14	−0.22	0.19	−0.32	−0.38	−0.72
diabetes	−3.97	−5.54	0.00	4.34	0.09	0.00	−0.15	−0.22	−0.24	−0.31	−0.62	−0.27	−0.87	−1.54	−0.44	−0.41	−0.71
mentalhealth	−4.40	−6.69	−0.06	3.59	0.86	0.74	0.43	0.59	0.52	0.25	0.37	0.22	0.11	2.56	−0.33	−0.60	−1.10
antithrombotic	−0.96	−11.85	−0.37	−0.51	−0.33	−0.59	−0.66	−0.69	−0.71	−0.78	−0.71	−0.92	−1.06	3.47	−0.39	−0.40	−0.70
cardiac	−1.22	−15.82	−0.73	−2.96	−0.32	−0.46	−0.53	−0.67	−0.64	−0.83	−0.83	−0.94	−0.99	−1.88	−0.59	−0.53	−0.93
parkinsons	−5.84	5.00	0.68	8.18	0.52	0.41	0.18	0.19	0.10	0.13	−0.21	0.02	−0.17	−7.37	−0.31	−0.58	−0.94

Figure 10: GLM coefficients for the medical and demographic variable model-Males. Darker colours indicate higher coefficient values for a given variable across health states.

Finalised Weighted GLM Coefficients - Female

Weighted proportional to observations (n/25,000)

Health State	alpha	m0	omega	m1	IRSAD 1	IRSAD 2	IRSAD 3	IRSAD 4	IRSAD 5	IRSAD 6	IRSAD 7	IRSAD 8	IRSAD 9	Home-owner	Married	Inc $500-999	Inc $1000+
healthy	−0.51	−27.98	−1.81	−11.42	−0.28	−0.54	−0.73	−0.79	−0.77	−0.96	−1.02	−1.14	−1.28	−7.20	−0.56	−0.82	−0.98
painmed	−0.75	−14.38	0.10	0.18	−0.08	−0.09	−0.32	−0.12	−0.16	−0.38	−0.15	−0.03	−0.09	−1.74	−0.30	−0.20	−0.41
diabetes	−2.94	−12.52	−0.48	0.74	0.16	0.04	−0.22	−0.30	−0.50	−0.39	−0.30	−0.62	−0.63	−0.01	−0.57	−0.51	−1.12
mentalhealth	−2.55	−17.47	−1.76	−6.85	0.05	0.19	0.05	0.07	−0.19	−0.06	−0.22	−0.21	−0.30	−0.26	−0.40	−0.51	−0.88
antithrombotic	−0.89	−18.90	−0.52	−0.91	0.68	0.49	0.22	0.21	0.30	0.31	0.11	0.10	0.00	1.05	−0.26	−0.42	−0.87
cardiac	−1.01	−19.79	−0.62	−1.63	−0.43	−0.62	−0.77	−0.82	−0.93	−1.00	−1.08	−1.15	−1.35	−4.84	−0.49	−0.54	−0.83
parkinsons	−3.27	−10.72	−1.06	−3.80	0.39	0.17	−0.10	0.07	−0.05	−0.13	−0.34	−0.27	−0.45	−3.69	−0.31	−0.58	−0.97

Figure 11: GLM coefficients for the medical and demographic variable model-Females. Darker colours indicate higher coefficient values for a given variable across health states.

Below, we categorise our findings first by health-state dynamics, and then by overarching variable impacts.

<u>Structural and Variable-Specific Impacts (Across Clusters)</u>

The fitted model reveals that the protective benefit of socio-economic status is not uniform; its magnitude is highly dependent on an individual's underlying medical cluster:

- **Mental Health vs. Acute Physical States:** The protective effect of area-based advantage (IRSAD) exhibits its strongest impact within the MH cluster. This suggests that survival and stability for psychological conditions are heavily reliant on community support, environmental stability, and access to local psychiatric infrastructure. Conversely, the IRSAD impact is noticeably weaker for acute physiological states like Cardiac or Antithrombotic, where mortality outcomes are driven more by immediate clinical intervention than by neighbourhood wealth.
- **Antithrombotic vs. Parkinson's Disease:** While home ownership generally acts as a strong protective buffer, its impact varies significantly by state. For transient or recovery states like Antithrombotic, home ownership produces a strong protective effect, likely as a stable, private environment is highly conducive to post-acute recovery. However, for progressive neurodegenerative conditions like Parkinson's Disease, this protective effect noticeably diminishes. This reflects the reality that retaining a traditional private home can become a physical liability compared to transitioning into specialised, accessible aged-care facilities.
- **Pain Medication:** The pain medication cluster (prescription-based) exhibits a unique profile, with individuals remaining in this state long-term facing a significant mortality spike. Furthermore, the lack of observed interaction with other medical indicators suggests this cohort primarily captures the trajectory of medically induced opioid addiction, rather than pain secondary to other modelled chronic diseases.
- **Impact of Marriage:** Being married offers the greatest protection against mortality in chronic and mobility impacting states (like Diabetes or Parkinson's Disease). In these situations, at-home caregiving from a spouse is often critical to survival. However, this protective effect is much weaker for purely short-term conditions.

<u>State-Specific Dynamics (Within Clusters)</u>

Looking across the entire state space, the demographic variables exhibit several consistent, structural behaviours:

- **IRSAD:** Higher socio-economic status provides a consistent protective buffer across all states. This is clearly demonstrated by the IRSAD coefficients, which exhibit a stable gradient were moving from decile 1 (most disadvantaged) to decile 9 (most advantaged) correlates with a progressive decrease in mortality risk.
- **Home ownership:** Home ownership is one of the most significant predictors of longevity. For example, in the Healthy female cluster, the home-owner coefficient is notably negative in sign and represents a significant reduction in the base force of mortality compared to non-homeowners.
- **Income Gradient:** There is a clear mortality reduction associated with higher earnings, with the $1000+ category consistently shows stronger protective effects (more negative coefficients) than the $500−999 bracket, particularly in high-volume states like Cardiac and Healthy.
- **Age-Related Convergence:** Due to the interaction with the $h_{00}(t)$ basis function, the fitted model captures socio-economic disparities as being the most influential at age 50, and naturally diminishing as individuals approach age 100 where biological senescence becomes the dominant driver of mortality.
- **Gender:** While the protective trends of wealth are universal, the magnitude of these coefficients varies between genders, reflecting distinct biological and socio-economic mortality trajectories that are now captured at a granular, health-state level.

5. Application of modelling results

The application of the modelling results will follow a similar structural approach to the foundational demographic analysis presented by Huang, Hui, and Villegas (2025). However, it adapts this application to the dynamic, multi-state realities of the integrated framework developed in 4.3 State Specific Demographic GLM.

5.1 Mortality Rates for Socio-Economic Profiles

Given specific values of IRSAD, home ownership, marital status, and income, the integrated modelling approach can be used to establish an underlying demographic parameter set. When combined with the multi-state medical transitions, we can then construct dynamic mortality rates and period life tables tailored to socio-economic profiles. As an illustration, four distinct profiles are established to evaluate the spectrum of socio-economic advantage:

- **Profile 1 (Low):** Single individual who is a non-homeowner, with an income of less than $499, and living in a D1 IRSAD area.
- **Profile 2a (Intermediate I):** Single individual who is a non-homeowner, with an income in $500-$999 bracket and living in a D5 IRSAD area.
- **Profile 2b (Intermediate II):** Married individual who is a homeowner, with an income in the $500–$999 bracket and living in a D5 IRSAD area.
- **Profile 3 (High):** Married individual who is a homeowner, with an income of more than $1000, and living in a D10 IRSAD area.

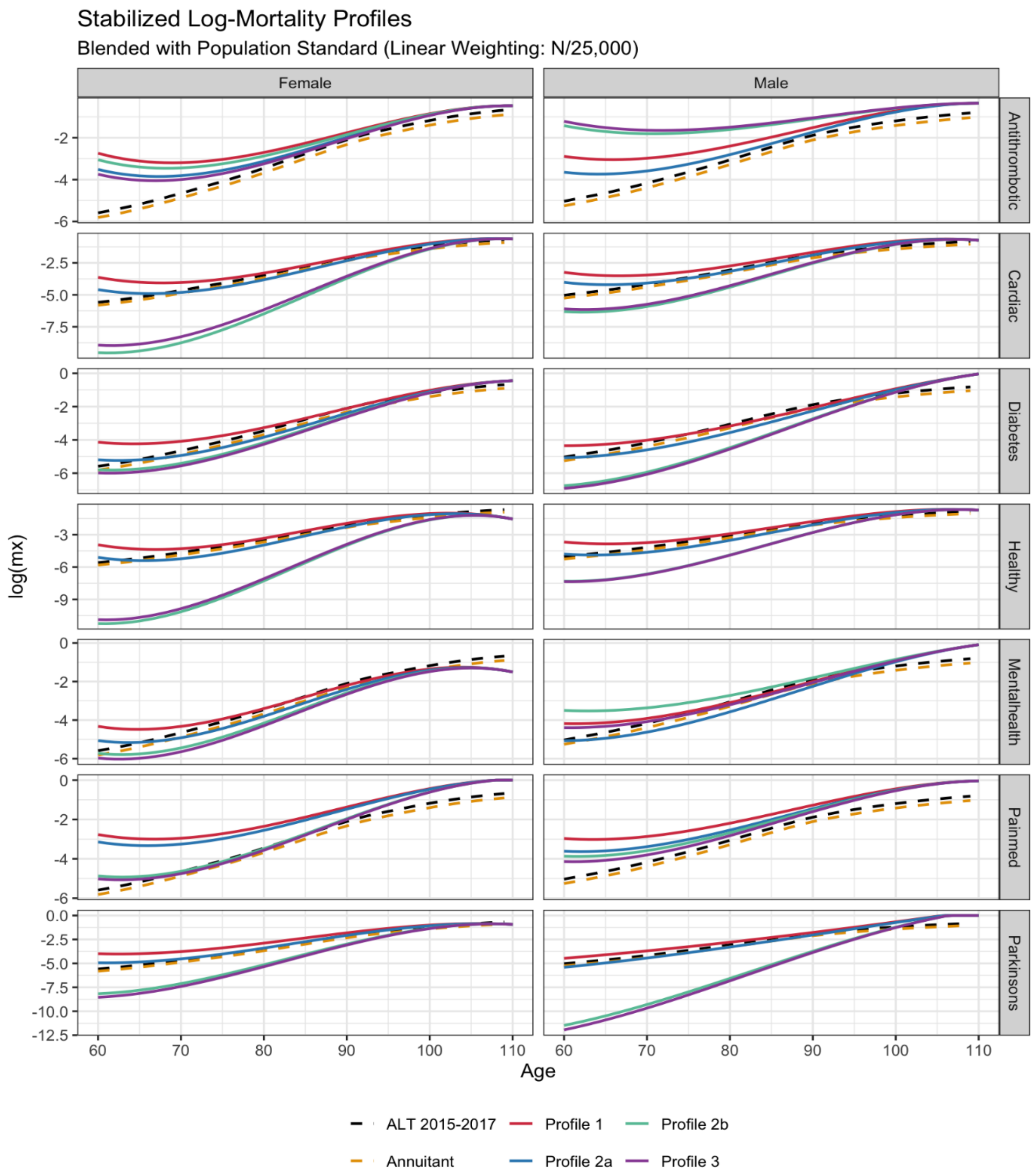


Figure 12: GLM mortality curves under the medical state-based Markov chain model for different socio-economic profiles.

The key findings from the above analysis are as follows:

- **Socioeconomic Gradient in Mortality:** Across all health conditions and both genders, a distinct socioeconomic gradient is evident. Profile 1 (representing the most disadvantaged individuals) consistently exhibits substantially higher mortality rates than the ALT 2015–2017 national baseline. Conversely, Profiles 2b and 3 (representing more advantaged individuals) demonstrate significantly lower mortality, reflecting the protective effects of higher socioeconomic status on longevity.
- Profile 2a generally aligns most closely with the ALT 2015–2017 rates, serving as a median representative of the Australian population.
- The impact of health states on the log-mortality curve varies by condition:
- Antithrombotic and Cardiac conditions show a higher baseline mortality at younger ages (60–70) compared to the Healthy state, though the curves tend to converge with the population standard as individuals reach extreme old age.

- For conditions like Parkinson's Disease and Diabetes, the mortality gap between the disadvantaged (Profile 1) and advantaged (Profile 3) is particularly pronounced at earlier ages, highlighting how socioeconomic resources may influence the management and progression of chronic illnesses.
- A significant deviance in mortality exists between the socially advantaged and disadvantaged females within the Healthy cluster. However, Healthy males do not seem to display such deviation. The significant mortality gap in Healthy females may be driven by differential healthcare utilisation; socially advantaged women often leverage higher health literacy and resources for preventative care and early intervention, whereas Healthy men traditionally exhibit more uniform, lower levels of engagement with primary health services.
- When considering individuals taking Antithrombotic medication, an unusual trend emerges males with higher socioeconomic status exhibit higher mortality rates compared to their lower socioeconomic counterparts. This counterintuitive finding warrants further investigation. One possible explanation is that individuals with higher socioeconomic status may receive antithrombotic therapy following more complex cardiovascular interventions, such as elective cardiac procedures. These patients often receive prolonged or intensified antithrombotic therapy due to higher baseline cardiovascular risk and procedural complexity (European Society of Cardiology (ESC) 2020).

6.2 Life Expectancy within the Markov Framework

To further gauge the magnitude of longevity differences in the Australian population at retirement age, period life expectancy at age 60 is computed for the different socio-economic profiles.

Unlike traditional static life tables where life expectancy is derived from a single, deterministic mortality curve (μ_x), calculating life expectancy in this integrated framework requires accounting for the dynamic nature of the Markov Chain. Because an individual's health will progressively deteriorate or change over time, their mortality risk shifts dynamically as they age.

To compute the period life expectancy (e_{60}) for a given socio-economic profile then, we develop the following calculation process:

- **State Space and Vector Definition**
  Let the finite state space S consist strictly of the 7 medical states under consideration $S = 1,2,3,4,5,6,7$. There is no death state in this matrix.

  We define a 1×7 row vector $\boldsymbol{S}(x)$ which represents the absolute probability distribution of an individual being alive and residing in each of the 6 states at exact age x.

  If evaluating a specific socio-economic profile starting at age 60 in state i (e.g., $i = 1$ for Healthy), the initial state vector is:

  $$S_{j(60)} = \begin{cases} 1 \text{ if } j = i \\ 0 \text{ if } j \neq i \end{cases}$$

- **The Competing Risk of Death (The Attrition Matrix)**
  Before any medical transitions occur, the model evaluates the risk of death. For any state i at age, the probability of death within the year is derived from the socio-economically adjusted GLM as:

  $$q_{i,x} = 1 - e(-\mu_{x,i})$$

  Consequently, the probability of surviving the year in state i is $p_{i,x} = 1 - q_{i,x}$.

To apply this mathematically across all states simultaneously, we construct a 7×7 diagonal survival matrix, $\boldsymbol{D}(x)$, where the diagonal elements are the state-specific survival probabilities, and all off-diagonal elements are zero:

$$\boldsymbol{D}(x) = \text{diag}(p_{1,x}, p_{2,x}, \dots, p_{6,x})$$

- **The Medical Transition Matrix**
  If the individual survives the mortality check, they then transition between the 6 living health states. Specifically, let $\boldsymbol{P}^*(x)$ denote the 7×7 transition matrix where each element $p^*_{ij}(x)$ is the conditional probability of moving from state i to state j, given that the individual has survived the year. Note because this matrix only distributes survivors among the living states, then the rows of $\boldsymbol{P}^*(x)$ sum exactly to one.
- **Recursive Survival Projection**
  To find the probability distribution of the cohort at the next age, we take the current state vector $s(x)$, apply the mortality factors for age x and the provided gender and disease $\boldsymbol{D}(x)$, $\boldsymbol{P}^*(x)$.
  The fundamental recursive equation for the integrated model is given by:

$$s(x+1) = s(x) \cdot \boldsymbol{D}(x) \cdot P^*(x)$$

  To project the trajectory of the cohort over years (from age 60 to age $60 + t$), this process is chained i.e.,

$$s(60+t) = s(60) \prod_{k=0}^{t-1} \left(\boldsymbol{D}(60+k) \cdot P^*(60+k)\right)$$

- **Period Life Expectancy Integration**
  Because death removes probability mass from the system via (x), the sum of the elements in the vector $s(60+t)$ naturally represents the total probability of being alive at age $60 + t$, denoted as ${}_tp_{60}$.
  Let $\mathbf{1}$ be a 7×1 column vector of ones. Then the absolute survival probability at duration t is the sum of the living states:

$${}_tp_{60} = s(60+t) \cdot \mathbf{1}$$

  Finally, the period life expectancy at age 60 (e_{60}) for that specific socio-economic profile is calculated by summing these total survival probabilities up to the limiting age of the life table ($x_1 = 110$, giving a maximum $t = 50$):

$$e_{60} = \sum_{t=1}^{50} {}_tp_{60} = \sum_{t=1}^{50} [s(60+t) \cdot \mathbf{1}]$$

  This formulation isolates mortality as an overarching, demographic-driven filter which governs survival, before the medical Markov chain dictates an individual's progressive deterioration.

By applying this methodology, period life expectancy was calculated across all socio-economic profiles for every initial state and gender combination. To isolate and quantify the specific impact of progressive health deterioration on longevity, these calculations were performed under two scenarios: a dynamic multi-state model (incorporating transitions) and a static single-state model. Given the extensive volume of data generated, only the results for the male 'pain medication' cohort are presented in the main text. The remaining tables are provided in the appendix (A2 Life Expectancy Plots).

For reference below, note the corresponding life expectancies are 29.1 years for females and 26.8 years for males, when using the ALT as a baseline comparison to see the impact of using the integrated framework above.

- **Transient and Persistent states**: The magnitude of the longevity gap between the static and dynamic tables reflects the clinical reality of the diseases:
  - Acute physical states (Cardiac) and crisis states (Pain Medication, MH) exhibit massive increases in life expectancy when dynamic transitions are enabled. This proves that many individuals successfully recover, manage, or transition out of these states rather than dying within them.
  - Conversely, the gap between static and dynamic projections is remarkably narrow for Diabetes and Parkinson's Disease. This confirms they function as highly persistent chronic conditions; once entered, individuals rarely transition back to baseline health.
- **The Underdiagnosis Effect:** The results reveal a notable statistical paradox where the life expectancies for Diabetes and MH frequently outperform the Healthy state and significantly exceed standard population baselines. This suggests a prominent Underdiagnosis Effect, where the Healthy cohort is contaminated by high-risk, undiagnosed individuals who avoid the medical system, while entry into a morbidity state acts as a proxy for healthcare engagement. Furthermore, while these states show high longevity, they rarely outperform the Healthy cohort in terms of life expectancy because the dynamic model accounts for high rates of healing and recovery seen; individuals in MH or managed Diabetes states often transition back toward the Healthy state within a year, hence not having a significant impact on the life expectancy.
- **The Universal Wealth and Advantage Gradients:** Across every single initial state and gender combination, higher personal income and area-based advantage (IRSAD) provide a consistent, progressive boost to longevity. Moving from the lowest deciles and income brackets to the highest yields a strict stair-step increase in life expectancy, confirming that financial and community wealth acts as a consistent buffer against mortality intensity, regardless of the baseline disease.
- **Impact of Marriage:** Across the entire state space, married individuals consistently exhibit higher life expectancies than their single counterparts. This quantifiable longevity advantage highlights the critical, life-extending impact of informal at-home caregiving and social support, particularly as individuals age and navigate progressive health deterioration.
- **The Complex Reality of Home Ownership (The Parkinson's Disease Reversal):** In almost all health states, home ownership emerges as a highly protective structural advantage. However, the data reveals an anomaly: in the dynamic Parkinson's Disease cohort, this trend narrows and often reverses, with advantaged non-homeowners occasionally outliving homeowners. This suggests that while a private home is beneficial for general ageing, retaining a traditional home becomes a physical liability-or limits access to specialised facility care-when dealing with severe, mobility-impeding neurodegenerative conditions. Note however that due to the low exposure, the weighting given to Parkinson’s Disease only mortality is low and remains a further improvement for the next iteration of the model.

Table 3:Life expectancy: Gender = Male, State = Pain medication, With transitions.

Male painMed (With Transitions)
Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	18.25	19.18	20.35	20.75	20.76	21.53	21.53	21.88	22.45	17.46
No	Married	21.94	22.75	23.76	24.08	24.09	24.74	24.74	25.03	25.51	21.26
Yes	Single	20.72	21.55	22.52	22.53	22.57	23.19	23.00	23.43	23.97	20.63
Yes	Married	23.12	23.95	24.81	24.82	24.88	25.44	25.24	25.70	26.22	22.94
500-999											
No	Single	21.72	22.53	23.54	23.88	23.89	24.54	24.55	24.85	25.34	21.00
No	Married	24.89	25.58	26.41	26.69	26.70	27.23	27.23	27.48	27.89	24.30
Yes	Single	23.23	24.05	24.89	24.92	24.97	25.52	25.33	25.79	26.30	22.97
Yes	Married	25.45	26.25	26.99	27.03	27.08	27.57	27.39	27.85	28.32	25.11
1000+											
No	Single	24.04	24.76	25.63	25.93	25.94	26.51	26.51	26.78	27.21	23.38
No	Married	26.82	27.41	28.12	28.37	28.38	28.84	28.84	29.06	29.42	26.29
Yes	Single	25.06	25.86	26.59	26.65	26.70	27.18	27.01	27.47	27.95	24.67
Yes	Married	27.13	27.89	28.53	28.59	28.64	29.07	28.90	29.35	29.79	26.69

Table 4: Life expectancy: Gender = Male, State = Pain medication, Without transitions.

Male painMed (Without Transitions)
Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	11.90	12.55	14.05	13.50	13.44	14.03	13.79	13.57	14.03	12.68
No	Married	13.91	14.56	16.03	15.50	15.44	16.01	15.78	15.57	16.01	14.69
Yes	Single	10.75	11.40	12.90	12.34	12.28	12.88	12.64	12.42	12.87	11.52
Yes	Married	12.76	13.41	14.90	14.36	14.30	14.88	14.64	14.43	14.88	13.53
500-999											
No	Single	14.27	14.92	16.38	15.85	15.79	16.36	16.13	15.92	16.36	15.04
No	Married	16.25	16.87	18.26	17.76	17.70	18.25	18.03	17.82	18.24	16.99
Yes	Single	13.12	13.77	15.26	14.72	14.66	15.24	15.00	14.79	15.24	13.90
Yes	Married	15.12	15.76	17.19	16.67	16.62	17.18	16.95	16.74	17.17	15.88
1000+											
No	Single	16.31	16.94	18.33	17.82	17.77	18.31	18.09	17.89	18.31	17.06
No	Married	18.20	18.79	20.09	19.62	19.57	20.07	19.87	19.68	20.07	18.90
Yes	Single	15.19	15.83	17.26	16.74	16.68	17.24	17.02	16.81	17.24	15.95
Yes	Married	17.13	17.74	19.09	18.60	18.55	19.07	18.86	18.67	19.07	17.85

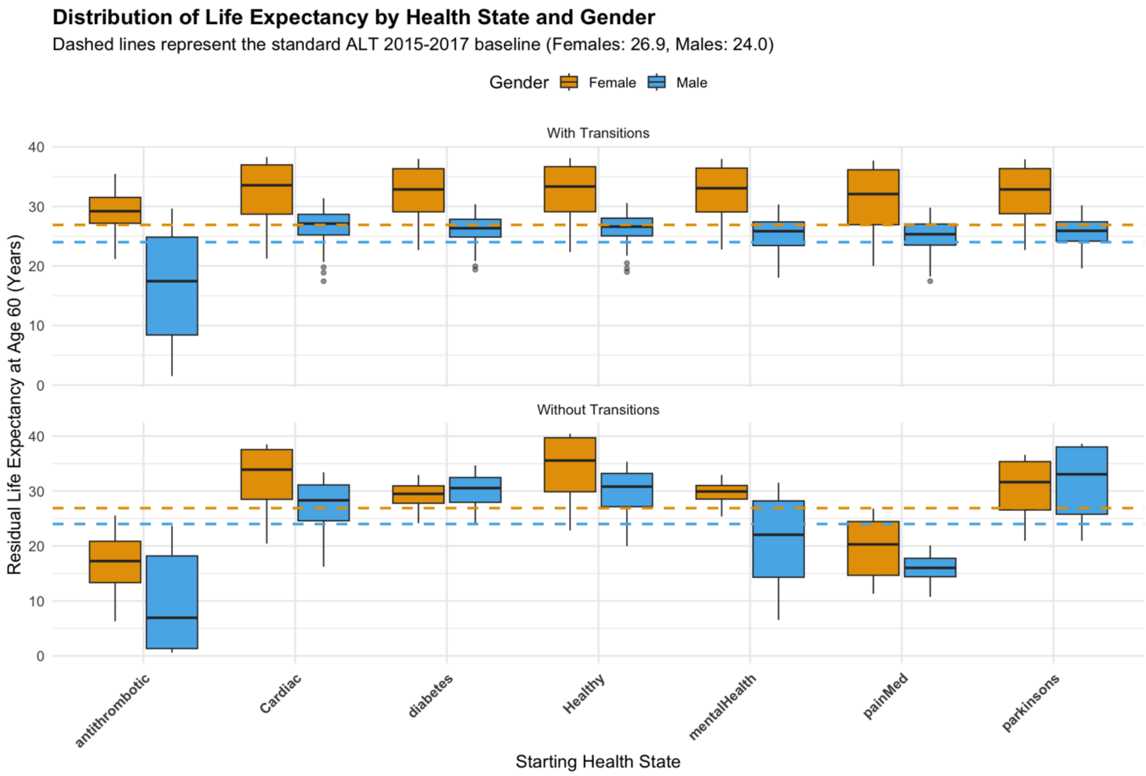


Figure 13: Distribution of life expectancy across gender and state- both with and without transitions.

6.3 Annuity Rates

To assess the financial consequences of socio-economic mortality disparities, a third analytical calculation was considered, namely the annual income generated by a life annuity. This calculation assumes a \$100,000 investment made by an individual aged 65 in 2016. To ensure the model remains relevant to future trends and for consistency, mortality improvement factors from the Australian Life Tables (ALT) 2015–2017 are integrated using a 125-year projection scenario (Australian Government Actuary 2017).

Assume an individual aged 65 belongs to a given socio-economic profile and begins in medical state i. Let $s(65)$ denote the initial state vector, where the probability is 1 for the starting state and 0 for all other states. For each future year, the cohort is projected forward by first applying state-specific survival probabilities and then allowing transitions between health states. Mortality improvement factors are incorporated into the survival probabilities. The projected state distribution at age $65 + t$ is therefore given by

$$s(65+t) = s(65)\prod_{k=0}^{t-1}\left(\boldsymbol{D}^{imp}(65+k)\cdot P^{*}(65+k)\right)$$

Where:

- $\boldsymbol{D}^{imp}(65+\mathrm{k})$ is the diagonal matrix of survival probabilities at age $65 + k$, adjusted for mortality improvement, i.e.,

$$\boldsymbol{D}^{imp}(x) = \left[p_{i,x}^{\text{imp}}\right]_{1_{i=j}}, \text{ where } p_{i,x}^{\text{imp}} = \exp\left(-\mu_{i,x}\left(1-\frac{I_x}{100}\right)^{t}\right)$$

- $\mathrm{P}^{*}(65+\mathrm{k})$ is the transition matrix between the living health states

The probability that the individual survives to age $65 + t$ is the sum of probabilities across all living states is given by:

$$_{t}p_{65} = s(65 + t) \cdot \mathbf{1}$$

where $\mathbf{1}$ is a column vector of ones.

The annuity factor for a one-dollar annual payment is then calculated as the discounted sum of these survival probabilities:

$$a_{65} = \sum_{t=1}^{110-65} \frac{_{t}p_{65}}{(1+r)^t}$$

where r is the annual interest rate.

Finally, for a $100,000 investment, the annual annuity income is calculated as

$$\frac{100000}{a_{65}}$$

This formulation allows annuity pricing to reflect dynamic health transitions, socio-economic differences, and mortality improvement, producing more accurate and equitable retirement income estimates.

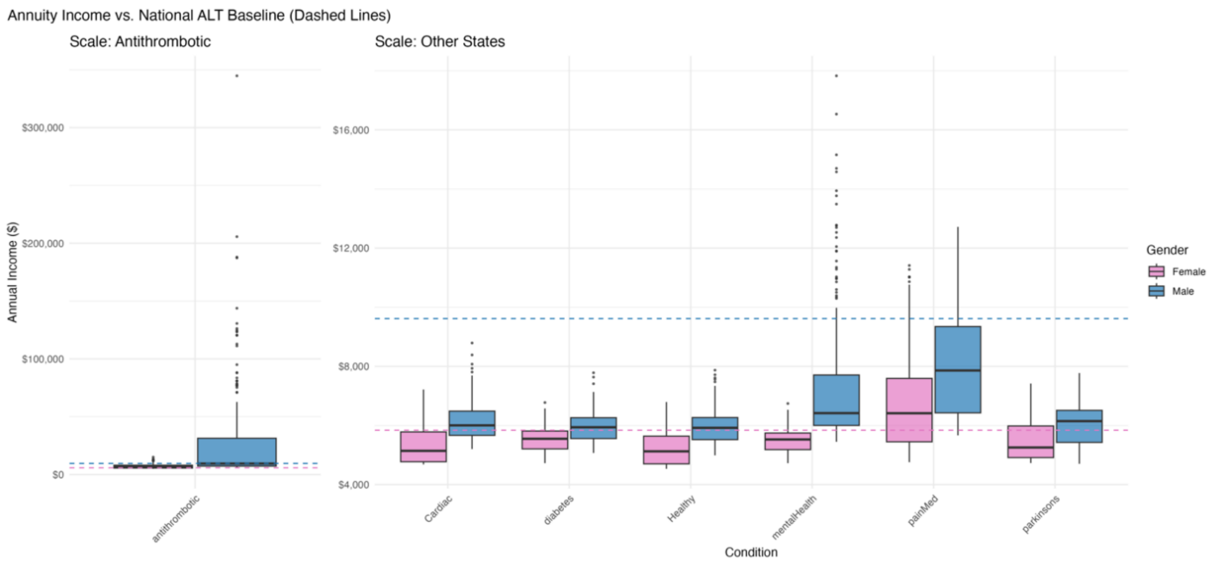


Figure 14: Analysis of annuity values against different states (note: Antithrombotic is displayed in a different axis due to its long tail nature).

As illustrated in Figure 14, the annual annuity income for a $100,000 investment is calculated as $\$100000 \,/\, a_{65,s,h,m,i}$, assuming a 3% interest rate ($r = 0.03$). *For context, baseline annuity incomes derived from the ALT 2015–2017 life tables are* $6,321 *for females and* $6,973 *for males. When adjusted using annuitant-specific mortality rates, these income figures decrease to* $5,956 *and* $6,381*, respectively.*

Given the extensive volume of data generated, only the results for the male 'pain medication' cohort are presented in the main text. The remaining tables are provided in the appendix (A3 Annuity calculations), noting no further analysis without transitions has been performed; this was only done for pain medication to understand the financial implication of the transitions.

Tables 6 and 7 present the annual income from a $100,000 investment into an annuity product for males taking pain medication (, from which some main findings can be drawn as follows:

Table 5: Annual income from a $100,000 investment into an annuity product: Gender = Male, State = Pain medication, Without transitions.

Annuity Income (Without Transitions) - Male - painMed

Home Ownership	Marital Status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	$11,761	$11,285	$10,343	$10,667	$10,704	$10,354	$10,493	$10,624	$10,355	$11,200
No	Married	$10,423	$10,061	$9,337	$9,587	$9,615	$9,346	$9,453	$9,554	$9,347	$9,995
Yes	Single	$12,718	$12,158	$11,053	$11,432	$11,476	$11,066	$11,229	$11,382	$11,068	$12,057
Yes	Married	$11,147	$10,724	$9,883	$10,173	$10,206	$9,894	$10,018	$10,135	$9,894	$10,648
500-999											
No	Single	$10,219	$9,873	$9,182	$9,421	$9,448	$9,190	$9,293	$9,389	$9,191	$9,811
No	Married	$9,241	$8,973	$8,433	$8,621	$8,642	$8,440	$8,520	$8,596	$8,441	$8,925
Yes	Single	$10,909	$10,506	$9,704	$9,980	$10,012	$9,714	$9,832	$9,944	$9,714	$10,433
Yes	Married	$9,773	$9,463	$8,842	$9,057	$9,081	$8,849	$8,941	$9,028	$8,850	$9,407
1000+											
No	Single	$9,211	$8,946	$8,410	$8,596	$8,617	$8,417	$8,496	$8,571	$8,417	$8,897
No	Married	$8,456	$8,248	$7,824	$7,971	$7,988	$7,829	$7,892	$7,952	$7,829	$8,209
Yes	Single	$9,738	$9,431	$8,815	$9,028	$9,052	$8,822	$8,914	$9,000	$8,823	$9,375
Yes	Married	$8,868	$8,628	$8,144	$8,312	$8,331	$8,150	$8,222	$8,290	$8,151	$8,585

Table 6 Annual income from a $100,000 investment into an annuity product: Gender = Male, State = Pain medication, With transitions.

Annuity Income (With Transitions) - Male - painMed

Home Ownership	Marital Status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	$8,263	$7,967	$7,619	$7,522	$7,520	$7,318	$7,320	$7,239	$7,100	$8,510
No	Married	$7,220	$7,026	$6,795	$6,733	$6,732	$6,596	$6,598	$6,543	$6,448	$7,376
Yes	Single	$7,465	$7,239	$6,993	$6,992	$6,984	$6,841	$6,883	$6,793	$6,677	$7,508
Yes	Married	$6,850	$6,670	$6,487	$6,487	$6,478	$6,370	$6,405	$6,327	$6,236	$6,899
500-999											
No	Single	$7,270	$7,071	$6,838	$6,771	$6,770	$6,631	$6,632	$6,575	$6,479	$7,439
No	Married	$6,564	$6,429	$6,269	$6,224	$6,223	$6,127	$6,128	$6,088	$6,020	$6,675
Yes	Single	$6,828	$6,650	$6,473	$6,469	$6,461	$6,355	$6,389	$6,312	$6,221	$6,891
Yes	Married	$6,364	$6,220	$6,086	$6,083	$6,076	$5,994	$6,022	$5,956	$5,884	$6,425
1000+											
No	Single	$6,734	$6,585	$6,410	$6,357	$6,356	$6,250	$6,251	$6,206	$6,131	$6,864
No	Married	$6,198	$6,094	$5,971	$5,935	$5,934	$5,859	$5,859	$5,827	$5,773	$6,286
Yes	Single	$6,440	$6,292	$6,154	$6,147	$6,140	$6,057	$6,085	$6,016	$5,942	$6,512
Yes	Married	$6,063	$5,943	$5,838	$5,832	$5,826	$5,761	$5,784	$5,726	$5,667	$6,129

Impact of transition

- Annuity income is consistently lower when transitions are included. Across all socio-economic groups, allowing for health state transitions reduces annuity payments compared to the static (no transition) model. Conversely, ignoring transitions overestimates longevity and annuity values, as the model without transitions assumes individuals remain in their initial health state, resulting in higher survival probabilities and inflated annuity income.
- Socio-economic differences remain but are smaller with transitions. The gradient across deprivation deciles (D1–D10), home ownership, and marital status persists, but the gap between groups is reduced when transitions are included. This impact is largest for healthier groups. Individuals starting in better health or higher socio-economic groups experience the largest reductions when transitions are introduced, reflecting the possibility of deterioration over time. Transitions also produce more conservative and realistic pricing, as incorporating movement between health states captures ageing and health deterioration, leading to more actuarially appropriate annuity estimates.

<u>Comparison between different states</u>

- Demographic factors produce a strong and very consistent annuity gradient within every medical state. Across both sexes, annuity income is generally highest for lower-income, non-homeowner, single, and more disadvantaged (low-decile) profiles, and lowest for higher-income, homeowner, married, and more advantaged profiles. This means the socio-economic effects remain visible even after conditioning on Medicare-defined health state.
- The Medicare-defined health states add a second layer of pricing differentiation on top of demographics. For females, the highest annuity incomes are usually seen in pain medication, antithrombotic, and some Parkinson's Disease/Cardiac profiles, while Healthy, Diabetes, and MH are often closer together. For males, pain medication and Cardiac tend to produce the highest annuity incomes among the stable states, with Healthy, Diabetes, MH, and Parkinson's Disease generally somewhat lower. In other words, the medical state materially shifts the annuity level but does not remove the demographic ordering.
- The total range captured by the integrated model is much wider than the single ALT-based annuity value.
- For females, the transition-based annuity tables span roughly $4,694 to $7,433, compared with the annuitant-adjusted ALT benchmark of $5,956. For males, the stable transition-based tables span roughly $5,403 to $8,899 (excluding the clear outlier seen for Antithrombotic males with a maximum income of $48,127), compared with the annuitant-adjusted ALT benchmark of $6,381.

Table 7: Range for different gender-state combinations

: The entries for anti-thrombotic males with homeownership should be viewed with caution due to potential data sparsity at extremes driving the GLM fit. This has been further detailed under* ***Analysis of Antithrombotic anomalies* *in the conclusion.*

Gender	Condition	Min Income	Max Income	Range
Female	Cardiac	4,694	7,065	2,371
Female	Healthy	4,711	6,795	2,084
Female	Antithrombotic	4,949	7,049	2,101
Female	Diabetes	4,727	6,776	2,049
Female	Mental Health	4,726	6,744	2,018
Female	Pain Medication	4,759	7,433	2,674
Female	Parkinson's Disease	4,730	6,831	2,101
Male	Cardiac	5,403	8,387	2,984
Male	Healthy	5,505	7,871	2,366
Male	Antithrombotic*	5,717	48,127	42,411

Male	Diabetes	5,536	7,783	2,247
Male	Mental Health	5,597	8,291	2,694
Male	Pain Medication	5,667	8,510	2,843
Male	Parkinson's Disease	5,631	7,774	2,143

- Relative to the ALT annuitant values, the model identifies both subsidised and underpriced groups. Many advantaged profiles fall below the ALT-based annuity income, implying longer expected survival than assumed by the standard annuitant table, while disadvantaged and higher-risk medical profiles fall well above it, implying shorter survival and therefore higher annual income. Overall, this suggest that the integrated Medicare and socio-economic approach can detect meaningful mortality variation that the ALT annuitant benchmark averages away.
- Most of the cross-sectional variation comes from demographics first, then health state, although the latter still matters materially. Within a given medical state, moving across income, home ownership, marital status, and deprivation decile often changes annual annuity income by many hundreds of dollars. Then, for a fixed demographic profile, moving across medical states typically adds another few hundred dollars, and in some cases more, especially for pain medication, cardiac, and Antithrombotic categories.
  There are signs of instability in some male Antithrombotic homeowner cells. The very large annuity incomes in those rows are far outside the rest of the tables and likely reflect sparse exposure or unstable estimates, so they should be interpreted cautiously.

In summary, compared with the ALT annuitant values of $5,956 for females and $6,381 for males, the transition-based integrated model demonstrates that annuity pricing can vary substantially once both socio-economic conditions and Medical-variable-defined states are incorporated. The standard annuitant table is a useful benchmark, but it materially understates the heterogeneity captured by the richer model.

Conclusion

This study advances the actuarial modelling of retiree mortality by integrating granular administrative health data (MBS and PBS records) with established socio-economic rating factors. By shifting from traditional static assumptions to a dynamic, multi-state Markov chain framework via an integrated GLM approach, we have demonstrated that modelling health as an evolving trajectory is essential for accurate longevity projections.

Methodologically, the use of binary medical indicators successfully mitigated the severe information leakage inherent in partial-year administrative counts. The resulting state-based architecture suggests that static pricing models systematically overestimate the longevity of initially Healthy individuals by ignoring inevitable deterioration and underestimate the survival of those in acute states by ignoring the potential for clinical recovery. Incorporating annual health transitions corrects these biases, yielding more conservative, actuarially sound life expectancies and annuity valuations.

Empirically, our findings confirm that mortality is driven by the complex interaction between biological health and systemic socio-economic access. While medical states provide a critical layer of risk differentiation, baseline demographic factors (particularly liquid income, home ownership, and geographic advantage) remain the dominant predictors of survival across almost all health conditions. The analysis also brought to light critical systemic nuances, notably the "underdiagnosis paradox" (where disadvantaged cohorts exhibit artificially low rates of diagnosed conditions due to barriers to healthcare access) and a pronounced, medically induced opioid mortality spike among affluent cohorts.

From a commercial and pricing perspective, the integrated model exposes the heterogeneity masked by aggregated national benchmarks. Compared to the single ALT annuitant baseline, our framework captures a massively widened spectrum of equitable annuity values. It successfully identifies both subsidised and underpriced cohorts, demonstrating that uniform pricing assumptions inadvertently penalise specific socio-economic and medical groups while exposing providers to significant adverse selection. By translating complex administrative data into interpretable, state-based risk categories, the proposed methodology can potentially bridge the gap between advanced health analytics and practical underwriting, enabling the design of fairer, more sustainable retirement income products.

7.1 Directions for Future Work

While this study establishes a robust foundation for health-integrated mortality modelling, data constraints and methodological simplifications highlight several key areas for future development. As broader and deeper longitudinal datasets become accessible, future iterations of the proposed model can focus on the following enhancements:

Data Linkage and Scope Expansion

- **Inclusion of Cancer and Terminal Illnesses:** Integrating state-based cancer registries and public hospital activity-based funding records to accurately capture intensive treatments (e.g., intravenous chemotherapy, radiation oncology) that are currently missing from outpatient MBS/PBS data.
- **Incorporation of Severe Medical Procedures:** Expanding the medical state space to include highly influential missing interventions, such as dialysis and neurosurgery.
- **Cause of Death Integration:** Linking explicit cause-of-death codes to individual records to move beyond all-cause mortality and analyse disease-specific terminal pathways.
- **Analysis of Antithrombotic anomalies:** The impact is particularly pronounced for males when stratified by home ownership, which may explain why the antithrombotic pattern differs from the trends observed in other plots. Notably, the range observed for males with home ownership appears unusually large. This may reflect data sparsity within this subgroup, where the GLM is primarily informed by centrally concentrated observations, with limited data at the extremes. Consequently, a small number of tail observations may exert disproportionate influence on the fitted relationship. Given the time constraints of the current analysis, this behaviour is flagged for further investigation in future work.

Longitudinal Depth and Disease Trajectories

- **Long-Tail Accuracy Testing:** Utilising extended observation windows (beyond the current 2011–2016 limit) to empirically validate the long-term accuracy of the Markov transition probabilities and expected lifetimes.
- **Capturing Complete Disease Progression:** Observing the full biological trajectory of chronic diseases, from baseline health to complex comorbidity, which currently unfolds over a timeframe longer than the existing data permits. This will allow us to relax the Markov Chain assumption on the medical state transitions, and better capture the risk of reemergence of conditions and allow for after recovery complications of certain conditions.
- **Modelling Marital Status Transitions**: Tracking the dynamic transition from "married" to "single" to explicitly isolate and price the severe physiological and psychological mortality shock associated with recent spousal loss (widowhood).

Methodological Enhancements

- **Detailed Variables:** Shifting from binary morbidity indicators back to a more detailed indicator of medical variables of information to quantify disease severity without triggering partial-year survival bias.
- **Refining Temporal Assumptions:** Releasing the simplifying assumption that age changes, transitions, and deaths occur strictly at the end of the calendar year, moving toward exact date-of-birth and date-of-death modelling.
- **Unweighted State-Specific Coefficients:** Removing the reliance on proportional weighting and population-wide averages, and ultimately deriving demographic GLM mortality estimates solely from the isolated data within each specific health cluster (particularly for currently sparse states like Parkinson's Disease).
- **Demographic Impacts on Transitions:** Due to data limitations, the impact of demographic variables on health state transition probabilities could not be robustly tested. With greater data availability, future iterations of the model aim to incorporate age and gender covariates directly into the transition matrices.

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Appendix

A1.1 Additional Plots for EDA

Educational level against medical variables

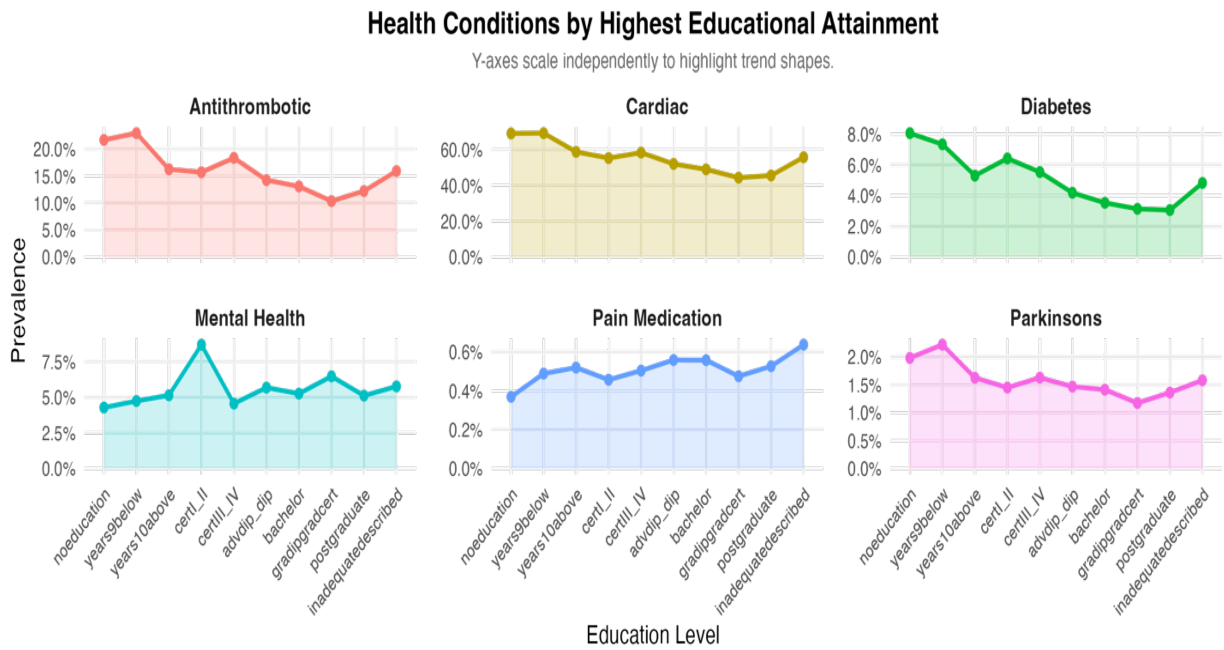


Figure 15: Relationship between the highest obtained education level and medical condition prevalence.

When evaluating specific medical conditions against educational attainment, the data reveals three distinct empirical trends. For cardiovascular and metabolic conditions (such as Cardiac Disease and Diabetes), the data shows a strict negative correlation: as educational attainment rises, disease prevalence steadily declines, confirming education as a robust proxy for preventative physical health. However, this demographic rule completely breaks down for psychological and pain-related conditions. For Mental Health indicators, the cohort with the least formal education records the absolute lowest disease prevalence in the dataset. Rather than indicating superior psychological health, we believe this result exposes a underdiagnosis paradox where less educated cohorts lack the resources to access formal psychiatric diagnoses and PBS-tracked medications. Finally, pain medication exposure completely inverts the standard demographic gradient, peaking among the most highly educated cohorts. This observation reflects the capacity of highly educated retirees to access major elective surgeries (which require strong post-operative opioids) and sustain ongoing prescription regimens.

Due to some noise in education data observed at retirement age this variable was not used for detailed modelling.

Educational level against medical variables

Most conditions, including Antithrombotic, Cardiac, Diabetes, and Parkinson’s, show higher prevalence among individuals with lower educational attainment, followed by a gradual decline as educational level increase. This pattern is consistent with the broader socioeconomic health gradient, where individuals with higher levels of education tend to experience better health outcomes. This may reflect improved health literacy, healthier lifestyle choices, greater access to preventive care, and increased ability to navigate healthcare systems.

The more granular groupings presented in this figure also reveal a slight increase in prevalence at the highest levels of educational attainment for some conditions. A possible explanation for this trend is increased health awareness and more frequent medical check-ups among highly educated individuals, which may lead to higher diagnosis and reporting rates rather than a true increase in underlying disease prevalence.

Overall, the figure highlights that educational attainment influences the prevalence of most medical conditions, although the magnitude and shape of these relationships vary slightly across conditions, reflecting differing underlying drivers such as health behaviours, access to care, and disease-specific characteristics.

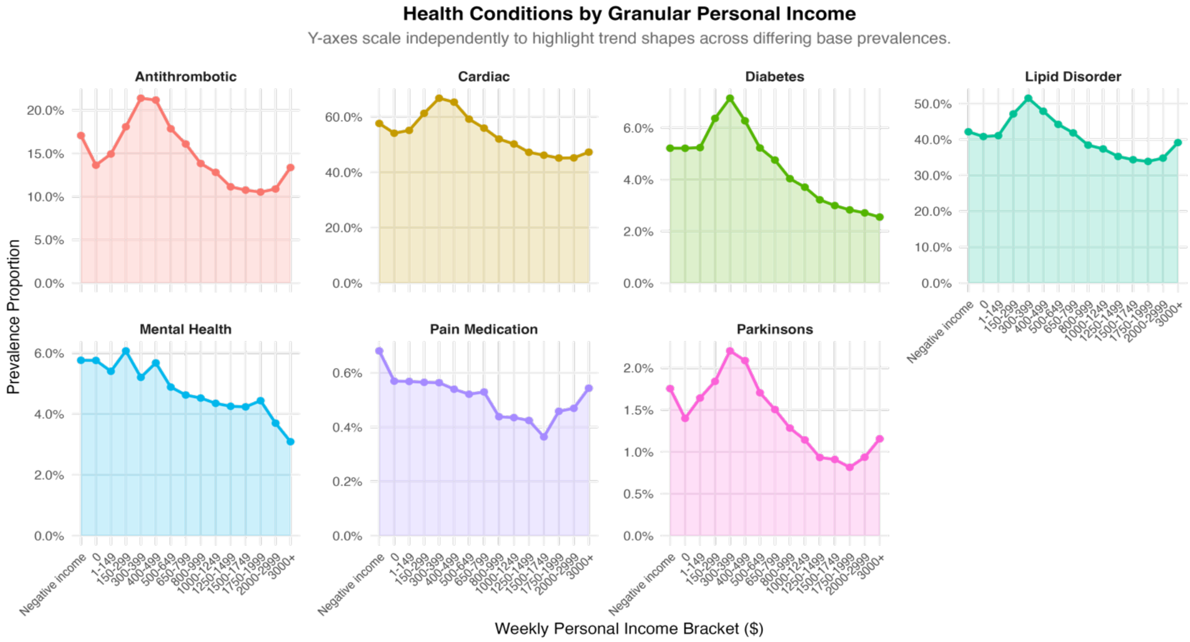


Figure 16:Mortality plots for each state against granular personal income categories.

A1.2 Additional Plots on Medicare Related Variables

Impact of transitions split by gender and age bins are shown in Figure 9 and Figure 10. These were used to derive conclusions in 4.1 Medical Variables Only Markov Chain Model.

Table 8: Difference in transition probabilities between males and females. The table denotes the difference calculated as Males-Females.

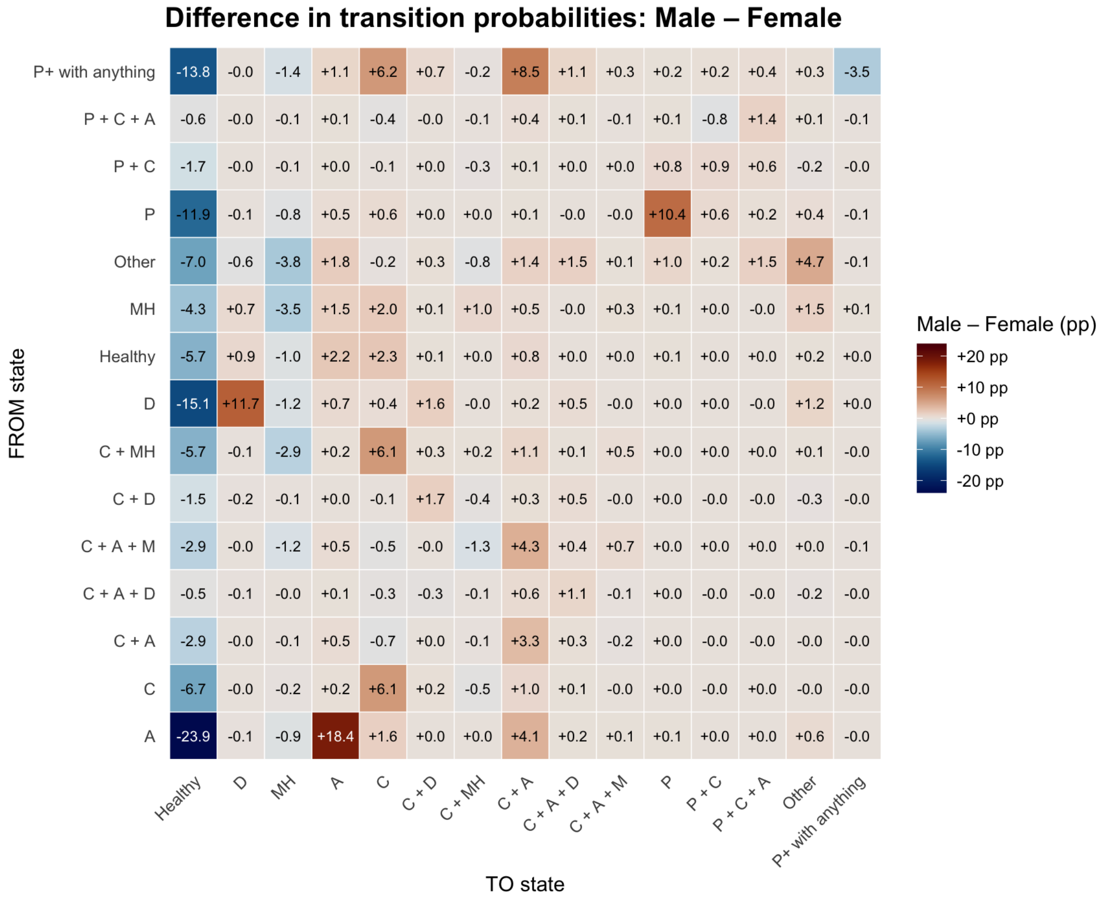
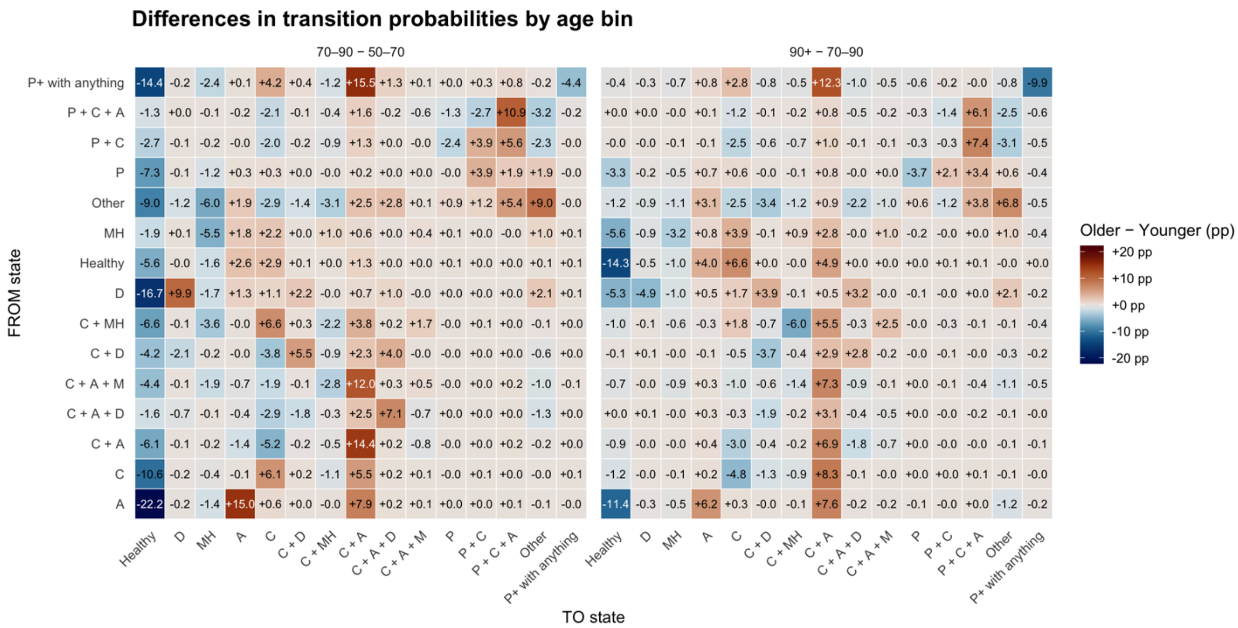


Table 9: Difference in transition probabilities between age bins 50-70, 70-90, and 90+. Each plot denotes the difference between older to younger bins.



A2 Life Expectancy Plots

Table 10: Average life expectancy for health states.

Mean Life Expectancy by Health State

Averaged across all demographic variables (With Transitions)

Initial Health State	Mean LE	Absolute Min	Absolute Max
Female			
Healthy	32.69	22.36	38.10
Cardiac	32.64	21.24	38.28
mentalHealth	32.54	22.78	37.98
diabetes	32.50	22.69	37.97
parkinsons	32.34	22.69	37.91
painMed	31.37	20.01	37.69
antithrombotic	29.30	21.16	35.48
Male			
Cardiac	26.61	17.44	31.38
Healthy	26.39	19.00	30.56
diabetes	26.26	19.38	30.36
parkinsons	25.76	19.60	30.18
mentalHealth	25.35	18.04	30.32
painMed	25.15	17.46	29.79
antithrombotic	16.90	1.53	29.64

Table 11: Life expectancy: Gender = Female, State = Antithrombotic (With Transitions)

Female antithrombotic (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	21.16	22.53	23.87	24.04	23.95	24.39	25.06	25.41	26.08	21.45
No	Married	23.80	25.00	26.16	26.30	26.23	26.60	27.19	27.48	28.06	24.11
Yes	Single	24.06	25.74	27.86	27.91	27.37	27.35	28.74	28.91	29.60	28.77
Yes	Married	26.54	28.04	29.90	29.95	29.48	29.47	30.68	30.83	31.43	30.64
500-999											
No	Single	24.77	25.88	26.97	27.10	27.05	27.39	27.93	28.21	28.76	24.99
No	Married	26.93	27.89	28.82	28.93	28.88	29.18	29.64	29.88	30.35	27.15
Yes	Single	27.77	29.16	30.87	30.91	30.50	30.49	31.59	31.74	32.30	31.49
Yes	Married	29.84	31.05	32.53	32.57	32.21	32.22	33.16	33.29	33.77	33.00
1000+											
No	Single	26.44	27.42	28.32	28.44	28.42	28.77	29.19	29.45	29.93	26.34
No	Married	28.37	29.20	29.97	30.08	30.06	30.36	30.72	30.94	31.35	28.31
Yes	Single	30.80	31.88	33.19	33.23	32.93	32.95	33.77	33.89	34.32	33.51
Yes	Married	32.46	33.38	34.49	34.53	34.28	34.31	35.00	35.11	35.48	34.71

Table 12: Life expectancy: Gender = Female, State = Antithrombotic (Without Transitions)

Female antithrombotic (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	13.77	15.23	17.24	17.27	16.63	16.55	17.98	18.10	18.77	18.78
No	Married	15.76	17.18	19.10	19.13	18.52	18.45	19.80	19.92	20.55	20.56
Yes	Single	6.30	7.50	9.35	9.38	8.76	8.69	10.10	10.22	10.92	10.93
Yes	Married	7.96	9.29	11.28	11.31	10.65	10.58	12.05	12.18	12.90	12.91
500-999											
No	Single	16.91	18.30	20.16	20.19	19.59	19.53	20.83	20.94	21.54	21.55
No	Married	18.79	20.10	21.84	21.86	21.31	21.25	22.46	22.56	23.11	23.12
Yes	Single	9.03	10.42	12.45	12.49	11.82	11.74	13.24	13.36	14.09	14.10
Yes	Married	10.94	12.39	14.45	14.48	13.81	13.74	15.23	15.35	16.07	16.08
1000+											
No	Single	20.12	21.37	23.01	23.03	22.51	22.45	23.59	23.68	24.21	24.21
No	Married	21.80	22.96	24.46	24.48	24.01	23.95	24.99	25.08	25.55	25.56
Yes	Single	12.41	13.88	15.93	15.96	15.30	15.22	16.69	16.81	17.51	17.52
Yes	Married	14.41	15.86	17.85	17.88	17.24	17.17	18.58	18.69	19.35	19.36

Table 13: Life expectancy: Gender = Female, State = Cardiac (With Transitions)

Female Cardiac (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	23.18	24.30	25.20	25.40	25.67	26.18	26.51	26.89	27.56	21.24
No	Married	25.76	26.69	27.45	27.62	27.83	28.25	28.53	28.85	29.40	24.18
Yes	Single	35.13	35.47	35.88	35.92	35.93	36.00	36.22	36.31	36.51	35.42
Yes	Married	35.88	36.18	36.55	36.59	36.60	36.66	36.86	36.94	37.12	36.14
500-999											
No	Single	26.36	27.26	27.98	28.14	28.35	28.76	29.02	29.32	29.86	24.82
No	Married	28.42	29.17	29.78	29.91	30.07	30.41	30.64	30.89	31.33	27.20
Yes	Single	36.13	36.43	36.78	36.81	36.82	36.89	37.07	37.16	37.33	36.36
Yes	Married	36.78	37.05	37.37	37.39	37.41	37.47	37.63	37.71	37.87	36.98
1000+											
No	Single	27.47	28.29	28.94	29.09	29.27	29.65	29.89	30.16	30.64	26.08
No	Married	29.34	30.02	30.57	30.69	30.83	31.15	31.35	31.58	31.98	28.24
Yes	Single	36.71	36.98	37.28	37.31	37.33	37.40	37.55	37.63	37.79	36.86
Yes	Married	37.30	37.54	37.82	37.84	37.86	37.92	38.06	38.14	38.28	37.42

Table 14: Life expectancy: Gender = Female, State = Cardiac (Without Transitions)

Female Cardiac (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	23.10	24.18	24.99	25.21	25.76	26.12	26.48	26.81	27.65	20.44
No	Married	25.70	26.60	27.28	27.46	27.92	28.22	28.52	28.80	29.49	23.44
Yes	Single	36.39	36.61	36.78	36.83	36.94	37.02	37.10	37.18	37.37	35.87
Yes	Married	36.93	37.13	37.28	37.32	37.43	37.50	37.57	37.64	37.81	36.46
500-999											
No	Single	25.97	26.86	27.52	27.70	28.15	28.44	28.73	29.00	29.68	23.76
No	Married	28.10	28.83	29.38	29.53	29.90	30.15	30.39	30.61	31.18	26.25
Yes	Single	36.99	37.19	37.34	37.38	37.48	37.55	37.62	37.69	37.86	36.53
Yes	Married	37.47	37.65	37.79	37.82	37.92	37.98	38.05	38.11	38.27	37.05
1000+											
No	Single	27.28	28.07	28.66	28.82	29.22	29.49	29.74	29.99	30.60	25.28
No	Married	29.18	29.84	30.33	30.46	30.80	31.01	31.23	31.43	31.94	27.53
Yes	Single	37.28	37.46	37.61	37.65	37.75	37.81	37.88	37.94	38.10	36.84
Yes	Married	37.73	37.90	38.03	38.07	38.16	38.22	38.28	38.34	38.49	37.34

Table 15: Life expectancy: Gender = Female, State = Diabetes (With Transitions)

Female diabetes (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	23.75	24.81	25.74	25.95	26.10	26.58	26.84	27.30	27.82	22.69
No	Married	26.21	27.10	27.87	28.04	28.15	28.56	28.80	29.16	29.60	25.32
Yes	Single	33.57	34.05	34.72	34.80	34.88	34.88	35.13	35.37	35.60	34.28
Yes	Married	34.74	35.16	35.72	35.78	35.82	35.84	36.08	36.25	36.46	35.34
500-999											
No	Single	26.90	27.73	28.47	28.63	28.75	29.12	29.34	29.68	30.10	26.07
No	Married	28.83	29.53	30.14	30.27	30.36	30.68	30.87	31.15	31.51	28.14
Yes	Single	35.03	35.44	35.97	36.03	36.08	36.10	36.32	36.50	36.70	35.58
Yes	Married	35.98	36.33	36.79	36.83	36.86	36.89	37.09	37.23	37.41	36.43
1000+											
No	Single	27.96	28.72	29.37	29.51	29.61	29.98	30.18	30.48	30.87	27.11
No	Married	29.70	30.34	30.89	31.00	31.08	31.39	31.57	31.81	32.15	29.00
Yes	Single	36.00	36.33	36.76	36.81	36.84	36.88	37.07	37.20	37.37	36.37
Yes	Married	36.78	37.07	37.44	37.47	37.50	37.54	37.71	37.82	37.97	37.08

Table 16: Life expectancy: Gender = Female, State = Diabetes (Without Transitions)

Female diabetes (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	24.15	24.77	26.02	26.38	27.26	26.80	26.39	27.75	27.79	24.96
No	Married	26.90	27.40	28.42	28.72	29.44	29.06	28.73	29.83	29.86	27.56
Yes	Single	24.21	24.82	26.06	26.43	27.30	26.84	26.44	27.79	27.83	25.01
Yes	Married	26.94	27.44	28.46	28.76	29.47	29.09	28.76	29.86	29.90	27.60
500-999											
No	Single	26.65	27.17	28.20	28.51	29.24	28.86	28.52	29.64	29.68	27.32
No	Married	28.93	29.36	30.20	30.45	31.05	30.73	30.45	31.37	31.40	29.48
Yes	Single	26.69	27.21	28.24	28.55	29.27	28.89	28.55	29.68	29.71	27.36
Yes	Married	28.97	29.39	30.23	30.48	31.07	30.76	30.48	31.40	31.43	29.52
1000+											
No	Single	29.05	29.47	30.31	30.55	31.14	30.83	30.56	31.47	31.49	29.60
No	Married	30.89	31.23	31.92	32.12	32.60	32.35	32.12	32.87	32.89	31.34
Yes	Single	29.09	29.51	30.34	30.58	31.17	30.86	30.59	31.49	31.52	29.63
Yes	Married	30.92	31.26	31.94	32.14	32.62	32.37	32.15	32.89	32.91	31.36

Table 17: Life expectancy: Gender = Female, State = Healthy (With Transitions)

Female Healthy (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	23.68	24.82	25.73	25.93	26.00	26.60	26.91	27.30	27.86	22.36
No	Married	26.18	27.12	27.88	28.04	28.10	28.59	28.85	29.17	29.63	25.12
Yes	Single	34.52	34.91	35.41	35.45	35.44	35.50	35.78	35.88	36.10	35.08
Yes	Married	35.36	35.71	36.17	36.20	36.19	36.24	36.49	36.58	36.78	35.84
500-999											
No	Single	26.99	27.86	28.56	28.71	28.78	29.22	29.46	29.76	30.20	26.00
No	Married	28.90	29.62	30.21	30.33	30.39	30.75	30.96	31.20	31.57	28.11
Yes	Single	35.66	36.00	36.43	36.46	36.46	36.51	36.75	36.84	37.03	36.10
Yes	Married	36.39	36.70	37.08	37.11	37.10	37.16	37.37	37.45	37.62	36.76
1000+											
No	Single	27.90	28.71	29.35	29.49	29.55	29.97	30.19	30.47	30.87	26.94
No	Married	29.68	30.34	30.88	31.00	31.05	31.40	31.58	31.81	32.16	28.90
Yes	Single	36.38	36.68	37.04	37.07	37.07	37.13	37.32	37.41	37.58	36.68
Yes	Married	37.03	37.29	37.62	37.64	37.65	37.70	37.88	37.95	38.10	37.27

Table 18: Life expectancy: Gender = Female, State = Healthy (Without Transitions)

Female Healthy (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	24.33	25.56	26.41	26.66	26.56	27.36	27.57	28.03	28.52	22.84
No	Married	26.89	27.89	28.58	28.78	28.71	29.35	29.53	29.91	30.30	25.67
Yes	Single	38.66	38.87	39.02	39.06	39.05	39.19	39.24	39.33	39.42	38.43
Yes	Married	39.11	39.30	39.44	39.48	39.46	39.60	39.64	39.72	39.82	38.89
500-999											
No	Single	27.89	28.80	29.43	29.61	29.54	30.14	30.30	30.64	31.00	26.78
No	Married	29.79	30.53	31.05	31.20	31.15	31.63	31.77	32.05	32.35	28.88
Yes	Single	39.30	39.48	39.62	39.66	39.64	39.78	39.82	39.90	39.99	39.09
Yes	Married	39.70	39.87	40.00	40.04	40.02	40.15	40.18	40.26	40.34	39.50
1000+											
No	Single	28.47	29.33	29.93	30.10	30.03	30.59	30.75	31.07	31.41	27.42
No	Married	30.26	30.97	31.46	31.60	31.55	32.01	32.14	32.41	32.70	29.41
Yes	Single	39.41	39.60	39.73	39.77	39.75	39.89	39.92	40.00	40.09	39.21
Yes	Married	39.81	39.98	40.10	40.14	40.12	40.25	40.28	40.36	40.44	39.61

Table 19: Life expectancy: Gender = Female, State = Mental Health (With Transitions)

Female mentalHealth (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	23.91	24.85	25.74	25.90	26.08	26.55	26.90	27.25	27.80	22.78
No	Married	26.28	27.08	27.83	27.97	28.11	28.51	28.80	29.10	29.56	25.36
Yes	Single	34.01	34.32	34.90	34.92	35.03	35.02	35.36	35.46	35.72	34.58
Yes	Married	34.99	35.30	35.80	35.82	35.89	35.91	36.20	36.29	36.51	35.50
500-999											
No	Single	27.03	27.77	28.47	28.60	28.75	29.11	29.39	29.66	30.10	26.15
No	Married	28.89	29.52	30.12	30.22	30.34	30.65	30.88	31.11	31.48	28.17
Yes	Single	35.33	35.62	36.09	36.12	36.19	36.20	36.48	36.57	36.78	35.78
Yes	Married	36.15	36.43	36.84	36.86	36.91	36.94	37.18	37.26	37.44	36.54
1000+											
No	Single	27.99	28.69	29.33	29.45	29.57	29.93	30.17	30.43	30.83	27.12
No	Married	29.71	30.31	30.84	30.95	31.04	31.34	31.55	31.76	32.11	29.00
Yes	Single	36.14	36.40	36.79	36.82	36.88	36.91	37.13	37.21	37.40	36.45
Yes	Married	36.86	37.10	37.44	37.47	37.51	37.55	37.74	37.81	37.98	37.11

Table 20: Life expectancy: Gender = Female, State = Mental Health (Without Transitions)

Female mentalHealth (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	26.10	25.38	26.11	26.00	27.24	26.60	27.35	27.33	27.72	26.34
No	Married	27.94	27.31	27.96	27.85	28.93	28.38	29.03	29.01	29.35	28.15
Yes	Single	27.32	26.65	27.33	27.22	28.36	27.78	28.45	28.44	28.80	27.53
Yes	Married	29.00	28.43	29.01	28.92	29.91	29.40	29.99	29.98	30.29	29.19
500-999											
No	Single	28.37	27.76	28.38	28.28	29.32	28.79	29.41	29.40	29.73	28.57
No	Married	29.92	29.39	29.93	29.84	30.75	30.28	30.83	30.81	31.10	30.09
Yes	Single	29.39	28.83	29.40	29.31	30.26	29.78	30.35	30.33	30.63	29.57
Yes	Married	30.81	30.32	30.81	30.73	31.57	31.14	31.64	31.63	31.89	30.96
1000+											
No	Single	29.81	29.28	29.82	29.73	30.65	30.18	30.73	30.72	31.01	29.99
No	Married	31.17	30.71	31.18	31.10	31.90	31.49	31.97	31.96	32.21	31.32
Yes	Single	30.71	30.22	30.72	30.64	31.48	31.05	31.55	31.54	31.80	30.87
Yes	Married	31.95	31.53	31.96	31.89	32.62	32.25	32.69	32.68	32.91	32.09

Table 21: Life expectancy: Gender = Female, State = Pain Medication (With Transitions)

Female painMed (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	21.49	22.42	23.66	23.42	23.66	24.56	24.36	24.38	25.06	20.01
No	Married	24.21	25.02	26.09	25.89	26.09	26.84	26.69	26.72	27.30	22.96
Yes	Single	33.81	34.20	34.84	34.75	34.76	34.95	35.08	35.10	35.36	34.26
Yes	Married	34.81	35.17	35.72	35.66	35.67	35.83	35.96	35.98	36.21	35.22
500-999											
No	Single	24.59	25.35	26.43	26.19	26.39	27.17	26.96	26.94	27.51	23.37
No	Married	26.89	27.55	28.46	28.26	28.43	29.08	28.92	28.92	29.41	25.88
Yes	Single	35.05	35.39	35.93	35.86	35.87	36.04	36.15	36.16	36.39	35.40
Yes	Married	35.92	36.23	36.70	36.64	36.66	36.80	36.91	36.93	37.13	36.23
1000+											
No	Single	25.91	26.62	27.59	27.39	27.57	28.27	28.10	28.11	28.63	24.76
No	Married	28.01	28.62	29.44	29.28	29.43	30.02	29.89	29.91	30.35	27.06
Yes	Single	35.86	36.16	36.62	36.56	36.58	36.74	36.82	36.84	37.04	36.09
Yes	Married	36.63	36.90	37.29	37.25	37.27	37.40	37.49	37.52	37.69	36.83

Table 22: Life expectancy: Gender = Female, State = Pain Medication (Without Transitions)

Female painMed (Without Transitions) Residual Life Expectancy at Age 60 (Years Left) up to age 110											
		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	11.87	11.89	13.45	12.13	12.38	13.87	12.29	11.49	11.89	11.30
No	Married	13.93	13.94	15.48	14.19	14.43	15.90	14.35	13.55	13.94	13.35
Yes	Single	22.52	22.54	23.64	22.71	22.89	23.93	22.83	22.24	22.54	22.10
Yes	Married	23.96	23.98	24.98	24.14	24.30	25.24	24.24	23.71	23.98	23.58
500-999											
No	Single	13.24	13.25	14.81	13.50	13.74	15.22	13.66	12.86	13.25	12.66
No	Married	15.27	15.29	16.80	15.53	15.77	17.20	15.69	14.90	15.29	14.71
Yes	Single	23.50	23.51	24.54	23.68	23.84	24.81	23.78	23.23	23.51	23.09
Yes	Married	24.84	24.86	25.79	25.01	25.16	26.03	25.11	24.61	24.86	24.48
1000+											
No	Single	14.65	14.67	16.19	14.91	15.15	16.60	15.07	14.28	14.67	14.08
No	Married	16.65	16.66	18.12	16.90	17.13	18.50	17.05	16.28	16.66	16.10
Yes	Single	24.44	24.46	25.42	24.61	24.77	25.67	24.71	24.20	24.46	24.07
Yes	Married	25.70	25.71	26.58	25.85	25.99	26.81	25.94	25.48	25.71	25.36

Table 23: Life expectancy: Gender = Female, State = Parkinson's (With Transitions)

Female parkinsons (With Transitions) Residual Life Expectancy at Age 60 (Years Left) up to age 110											
		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	23.31	24.45	25.46	25.47	25.67	26.18	26.63	26.90	27.53	22.69
No	Married	25.65	26.63	27.50	27.51	27.68	28.11	28.50	28.73	29.26	25.13
Yes	Single	33.75	34.25	34.87	34.90	34.86	34.91	35.28	35.38	35.64	34.61
Yes	Married	34.71	35.16	35.71	35.74	35.70	35.76	36.08	36.17	36.40	35.46
500-999											
No	Single	26.51	27.41	28.22	28.24	28.40	28.80	29.14	29.37	29.86	25.96
No	Married	28.39	29.16	29.85	29.87	30.00	30.34	30.64	30.83	31.25	27.93
Yes	Single	35.09	35.51	36.03	36.06	36.03	36.08	36.38	36.47	36.69	35.76
Yes	Married	35.92	36.29	36.75	36.78	36.75	36.80	37.06	37.14	37.34	36.48
1000+											
No	Single	27.66	28.47	29.18	29.23	29.35	29.73	30.02	30.24	30.68	27.04
No	Married	29.38	30.07	30.67	30.71	30.82	31.14	31.39	31.58	31.96	28.86
Yes	Single	35.98	36.33	36.76	36.78	36.77	36.83	37.07	37.15	37.34	36.44
Yes	Married	36.69	37.01	37.39	37.41	37.40	37.46	37.67	37.74	37.91	37.08

Table 24: Life expectancy: Gender = Female, State = Parkinson's (Without Transitions)

Female parkinsons (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	20.94	22.13	23.51	22.63	23.28	23.63	24.63	24.31	25.12	23.01
No	Married	22.59	23.68	24.95	24.14	24.73	25.06	25.96	25.68	26.42	24.49
Yes	Single	33.49	33.88	34.35	34.05	34.27	34.39	34.73	34.62	34.90	34.18
Yes	Married	34.04	34.41	34.84	34.56	34.76	34.88	35.19	35.09	35.35	34.68
500-999											
No	Single	23.95	24.96	26.13	25.39	25.93	26.23	27.06	26.79	27.47	25.70
No	Married	25.35	26.27	27.33	26.65	27.15	27.42	28.17	27.93	28.55	26.94
Yes	Single	34.50	34.84	35.25	34.99	35.18	35.28	35.58	35.48	35.73	35.10
Yes	Married	34.98	35.30	35.68	35.43	35.61	35.71	35.99	35.90	36.13	35.54
1000+											
No	Single	25.71	26.60	27.64	26.98	27.46	27.72	28.46	28.22	28.82	27.26
No	Married	26.95	27.76	28.70	28.10	28.54	28.77	29.44	29.23	29.77	28.36
Yes	Single	35.10	35.42	35.79	35.55	35.72	35.82	36.09	36.00	36.23	35.65
Yes	Married	35.54	35.83	36.18	35.96	36.12	36.21	36.47	36.38	36.60	36.05

Table 25: Life expectancy: Gender = Male, State = Antithrombotic (With Transitions)

Male antithrombotic (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	18.07	19.27	20.33	20.80	20.90	21.55	21.48	22.16	22.86	16.71
No	Married	21.89	22.92	23.80	24.19	24.27	24.82	24.77	25.34	25.91	20.68
Yes	Single	2.61	3.87	4.37	4.54	4.66	5.18	4.70	6.17	7.24	1.53
Yes	Married	4.84	6.67	7.34	7.57	7.73	8.40	7.79	9.64	10.91	3.05
500-999											
No	Single	21.61	22.66	23.55	23.95	24.03	24.59	24.54	25.11	25.68	20.39
No	Married	24.88	25.74	26.46	26.79	26.85	27.32	27.28	27.74	28.20	23.85
Yes	Single	4.86	6.70	7.38	7.60	7.76	8.43	7.82	9.67	10.94	3.06
Yes	Married	8.00	10.27	11.08	11.34	11.52	12.29	11.60	13.66	15.01	5.53
1000+											
No	Single	23.92	24.83	25.61	25.96	26.03	26.52	26.48	26.97	27.46	22.83
No	Married	26.77	27.52	28.14	28.43	28.48	28.89	28.85	29.25	29.64	25.88
Yes	Single	7.20	9.39	10.17	10.43	10.61	11.35	10.67	12.70	14.04	4.86
Yes	Married	10.88	13.35	14.20	14.47	14.66	15.45	14.74	16.83	18.16	8.01

The impact is particularly pronounced for males when stratified by home ownership, which may explain why the antithrombotic pattern differs from the trends observed in other plots. Notably, the range observed for males with home ownership appears to show significant deviation. This may reflect data sparsity within this subgroup, where the GLM is primarily informed by centrally concentrated observations, with limited data at the lower extremes. Consequently, a small number of tail observations may exert disproportionate influence on the fitted relationship. Given the time constraints of the current analysis, this behaviour is flagged for further investigation in future work.

Table 26: Life expectancy: Gender = Male, State = Antithrombotic (Without Transitions)

Male antithrombotic (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	12.60	14.35	14.85	15.03	15.15	15.63	15.13	16.56	17.45	10.37
No	Married	15.27	16.98	17.45	17.62	17.74	18.19	17.72	19.06	19.88	13.02
Yes	Single	0.69	0.82	0.86	0.88	0.89	0.95	0.89	1.06	1.20	0.59
Yes	Married	0.91	1.12	1.20	1.23	1.25	1.33	1.24	1.52	1.74	0.72
500-999											
No	Single	15.29	17.00	17.47	17.64	17.76	18.20	17.74	19.08	19.90	13.04
No	Married	17.87	19.47	19.90	20.06	20.17	20.58	20.15	21.38	22.12	15.71
Yes	Single	0.91	1.13	1.20	1.23	1.25	1.33	1.25	1.53	1.74	0.72
Yes	Married	1.27	1.62	1.74	1.79	1.82	1.95	1.82	2.25	2.58	0.95
1000+											
No	Single	17.28	18.90	19.35	19.51	19.62	20.04	19.60	20.86	21.62	15.09
No	Married	19.73	21.22	21.62	21.77	21.87	22.24	21.85	22.98	23.66	17.68
Yes	Single	1.17	1.48	1.59	1.63	1.66	1.78	1.66	2.05	2.35	0.89
Yes	Married	1.69	2.19	2.35	2.42	2.46	2.64	2.45	3.05	3.49	1.24

Table 27: Life expectancy: Gender = Male, State = Cardiac (With Transitions)

Male Cardiac (With Transitions)
Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	18.87	19.79	20.68	21.33	21.30	22.15	22.21	22.69	23.19	17.44
No	Married	22.66	23.45	24.20	24.72	24.71	25.40	25.44	25.83	26.25	21.49
Yes	Single	24.10	24.77	25.35	25.56	25.61	26.12	26.01	26.48	26.88	23.61
Yes	Married	26.14	26.78	27.31	27.48	27.53	27.97	27.86	28.32	28.70	25.69
500-999											
No	Single	22.30	23.10	23.87	24.41	24.39	25.10	25.14	25.54	25.96	21.09
No	Married	25.52	26.17	26.81	27.23	27.22	27.78	27.82	28.14	28.48	24.56
Yes	Single	26.12	26.76	27.28	27.46	27.51	27.95	27.84	28.30	28.67	25.60
Yes	Married	27.96	28.57	29.04	29.19	29.23	29.62	29.51	29.94	30.29	27.47
1000+											
No	Single	24.54	25.23	25.91	26.38	26.37	26.97	27.01	27.35	27.72	23.50
No	Married	27.33	27.89	28.45	28.81	28.81	29.28	29.31	29.58	29.89	26.52
Yes	Single	27.52	28.14	28.61	28.78	28.82	29.21	29.11	29.54	29.90	26.98
Yes	Married	29.22	29.81	30.23	30.37	30.41	30.76	30.65	31.06	31.38	28.72

Table 28: Life expectancy: Gender = Male, State = Cardiac (Without Transitions)

Male Cardiac (Without Transitions)
Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	18.34	19.24	19.70	20.52	20.32	21.44	21.48	22.05	22.33	16.23
No	Married	21.91	22.68	23.08	23.76	23.60	24.54	24.57	25.04	25.27	20.07
Yes	Single	27.78	28.28	28.53	28.98	28.87	29.47	29.49	29.80	29.94	26.56
Yes	Married	29.72	30.13	30.34	30.70	30.61	31.11	31.12	31.37	31.49	28.73
500-999											
No	Single	21.53	22.31	22.72	23.42	23.25	24.21	24.24	24.72	24.96	19.65
No	Married	24.60	25.26	25.59	26.17	26.03	26.81	26.84	27.24	27.43	23.03
Yes	Single	29.52	29.94	30.15	30.52	30.43	30.93	30.95	31.21	31.33	28.50
Yes	Married	31.14	31.49	31.66	31.97	31.90	32.31	32.33	32.54	32.64	30.31
1000+											
No	Single	23.68	24.38	24.73	25.35	25.20	26.04	26.07	26.49	26.69	22.01
No	Married	26.39	26.95	27.24	27.75	27.63	28.31	28.33	28.67	28.84	25.01
Yes	Single	30.66	31.02	31.21	31.54	31.46	31.90	31.91	32.14	32.25	29.78
Yes	Married	32.08	32.39	32.54	32.81	32.75	33.12	33.13	33.32	33.41	31.36

Table 29: Life expectancy: Gender = Male, State = Diabetes (With Transitions)

Male diabetes (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	19.97	20.81	21.93	22.39	22.49	23.07	23.20	23.48	24.18	19.38
No	Married	23.54	24.25	25.15	25.53	25.60	26.08	26.18	26.43	26.98	23.02
Yes	Single	22.24	22.98	23.69	23.79	23.89	24.41	24.25	24.80	25.33	22.17
Yes	Married	24.29	25.05	25.70	25.78	25.88	26.37	26.20	26.77	27.27	24.10
500-999											
No	Single	23.23	23.96	24.87	25.26	25.34	25.83	25.93	26.18	26.74	22.68
No	Married	26.21	26.81	27.53	27.84	27.90	28.30	28.38	28.59	29.03	25.73
Yes	Single	24.38	25.14	25.76	25.87	25.96	26.42	26.26	26.82	27.32	24.09
Yes	Married	26.32	27.08	27.64	27.74	27.82	28.25	28.08	28.64	29.10	25.93
1000+											
No	Single	25.29	25.93	26.71	27.05	27.11	27.54	27.63	27.85	28.33	24.78
No	Married	27.87	28.39	29.00	29.28	29.32	29.68	29.74	29.93	30.31	27.44
Yes	Single	25.92	26.67	27.23	27.35	27.43	27.85	27.70	28.24	28.71	25.48
Yes	Married	27.77	28.50	29.00	29.11	29.19	29.57	29.41	29.94	30.36	27.27

Table 30: Life expectancy: Gender = Male, State = Diabetes (Without Transitions)

Male diabetes (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	23.80	24.27	24.98	25.30	25.39	25.74	27.07	25.56	28.03	24.25
No	Married	25.90	26.32	26.93	27.20	27.28	27.59	28.73	27.43	29.56	26.30
Yes	Single	30.01	30.29	30.71	30.90	30.95	31.16	31.94	31.05	32.52	30.28
Yes	Married	31.26	31.50	31.86	32.03	32.07	32.25	32.93	32.16	33.43	31.49
500-999											
No	Single	25.75	26.17	26.79	27.07	27.15	27.45	28.61	27.30	29.45	26.15
No	Married	27.59	27.95	28.49	28.73	28.80	29.06	30.05	28.92	30.78	27.94
Yes	Single	31.17	31.41	31.78	31.95	31.99	32.18	32.86	32.08	33.37	31.40
Yes	Married	32.26	32.47	32.79	32.93	32.97	33.13	33.73	33.05	34.17	32.46
1000+											
No	Single	27.04	27.42	27.98	28.23	28.30	28.58	29.62	28.44	30.38	27.40
No	Married	28.71	29.03	29.51	29.73	29.79	30.03	30.92	29.90	31.58	29.01
Yes	Single	31.93	32.15	32.49	32.64	32.68	32.84	33.47	32.76	33.93	32.14
Yes	Married	32.92	33.11	33.40	33.53	33.57	33.72	34.26	33.64	34.67	33.10

Table 31: Life expectancy: Gender = Male, State = Healthy (With Transitions)

Male Healthy (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

Home ownership	Marital status	IRSAD D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	19.59	20.48	21.72	22.20	22.32	22.89	22.97	23.35	23.97	19.00
No	Married	23.43	24.16	25.12	25.51	25.59	26.07	26.12	26.43	26.92	22.90
Yes	Single	22.58	23.31	24.03	24.13	24.24	24.75	24.58	25.14	25.63	22.52
Yes	Married	24.65	25.38	26.03	26.11	26.21	26.69	26.51	27.07	27.54	24.46
500-999											
No	Single	23.09	23.84	24.82	25.22	25.31	25.79	25.85	26.17	26.67	22.54
No	Married	26.21	26.82	27.57	27.88	27.95	28.34	28.38	28.64	29.03	25.74
Yes	Single	24.73	25.46	26.08	26.19	26.28	26.74	26.57	27.13	27.59	24.45
Yes	Married	26.65	27.37	27.93	28.03	28.11	28.53	28.36	28.90	29.33	26.28
1000+											
No	Single	25.25	25.89	26.72	27.07	27.14	27.56	27.61	27.88	28.31	24.73
No	Married	27.91	28.43	29.07	29.34	29.39	29.74	29.77	30.00	30.33	27.48
Yes	Single	26.24	26.97	27.53	27.64	27.73	28.13	27.98	28.51	28.95	25.83
Yes	Married	28.06	28.76	29.26	29.36	29.44	29.81	29.66	30.17	30.56	27.59

Table 32: Life expectancy: Gender = Male, State = Healthy (Without Transitions)

Male Healthy (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

Home ownership	Marital status	IRSAD D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	20.18	21.02	22.55	23.02	23.23	23.63	23.77	24.04	24.75	19.99
No	Married	24.36	25.03	26.22	26.58	26.74	27.05	27.16	27.36	27.91	24.21
Yes	Single	29.93	30.33	31.04	31.27	31.36	31.55	31.62	31.74	32.07	29.84
Yes	Married	31.89	32.20	32.76	32.94	33.01	33.16	33.21	33.31	33.58	31.82
500-999											
No	Single	23.92	24.61	25.83	26.21	26.38	26.70	26.81	27.02	27.58	23.76
No	Married	27.27	27.80	28.74	29.03	29.15	29.40	29.48	29.64	30.07	27.15
Yes	Single	31.68	32.00	32.58	32.76	32.84	32.99	33.04	33.14	33.42	31.61
Yes	Married	33.27	33.52	33.99	34.13	34.20	34.32	34.36	34.44	34.67	33.21
1000+											
No	Single	26.15	26.73	27.76	28.08	28.22	28.49	28.59	28.76	29.24	26.01
No	Married	28.98	29.42	30.22	30.46	30.57	30.78	30.85	30.98	31.35	28.88
Yes	Single	32.73	33.01	33.51	33.66	33.73	33.86	33.91	34.00	34.24	32.67
Yes	Married	34.11	34.33	34.74	34.87	34.93	35.04	35.07	35.15	35.34	34.06

Table 33: Life expectancy: Gender = Male, State = Mental Health (With Transitions)

Male mentalHealth (With Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	19.93	20.78	21.97	22.36	22.48	23.10	23.13	23.53	24.13	19.58
No	Married	23.49	24.21	25.16	25.48	25.57	26.10	26.11	26.45	26.93	23.17
Yes	Single	18.04	19.06	20.61	20.21	20.52	21.73	21.25	22.14	22.84	20.35
Yes	Married	20.81	21.81	23.19	22.86	23.14	24.21	23.77	24.61	25.27	22.65
500-999											
No	Single	23.27	24.00	24.95	25.29	25.38	25.90	25.93	26.26	26.74	22.88
No	Married	26.23	26.82	27.58	27.85	27.92	28.35	28.36	28.64	29.02	25.89
Yes	Single	21.68	22.63	23.85	23.62	23.85	24.79	24.41	25.19	25.80	23.04
Yes	Married	24.14	25.06	26.12	25.94	26.14	26.96	26.62	27.35	27.90	25.13
1000+											
No	Single	25.37	26.00	26.81	27.11	27.19	27.63	27.66	27.94	28.36	24.97
No	Married	27.92	28.43	29.07	29.31	29.37	29.74	29.75	29.99	30.32	27.58
Yes	Single	24.14	25.02	26.00	25.88	26.07	26.81	26.51	27.21	27.75	24.87
Yes	Married	26.35	27.19	28.04	27.96	28.11	28.76	28.48	29.13	29.61	26.81

Table 34: Life expectancy: Gender = Male, State = Mental Health (Without Transitions)

Male mentalHealth (Without Transitions)

Residual Life Expectancy at Age 60 (Years Left) up to age 110

		IRSAD									
Home ownership	Marital status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	22.81	23.45	24.96	24.22	24.56	25.82	25.26	25.94	26.42	26.88
No	Married	24.49	25.07	26.43	25.76	26.07	27.20	26.70	27.31	27.74	28.15
Yes	Single	6.55	7.22	9.04	8.09	8.52	10.24	9.44	10.42	11.16	11.90
Yes	Married	8.43	9.19	11.17	10.15	10.61	12.44	11.61	12.63	13.39	14.15
500-999											
No	Single	25.77	26.31	27.55	26.93	27.22	28.25	27.79	28.35	28.74	29.11
No	Married	27.16	27.64	28.75	28.20	28.45	29.37	28.97	29.46	29.81	30.14
Yes	Single	10.17	10.98	13.05	11.99	12.47	14.33	13.49	14.52	15.28	16.03
Yes	Married	12.37	13.21	15.30	14.24	14.72	16.56	15.73	16.75	17.49	18.20
1000+											
No	Single	27.84	28.29	29.33	28.82	29.05	29.92	29.54	30.00	30.33	30.65
No	Married	29.00	29.41	30.34	29.88	30.09	30.87	30.52	30.94	31.24	31.52
Yes	Single	13.56	14.41	16.48	15.43	15.91	17.72	16.91	17.90	18.62	19.31
Yes	Married	15.81	16.64	18.63	17.63	18.09	19.81	19.04	19.97	20.65	21.29

A3 Annuity calculations

Table 35: Annual income from a $100,000 investment into an annuity product: Gender = Female, State = Antithrombotic, With Transitions.

Annuity Income (With Transitions) - Female - antithrombotic											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$7,049	$6,770	$6,522	$6,491	$6,503	$6,422	$6,310	$6,250	$6,141	$7,014
No	Married	$6,524	$6,316	$6,129	$6,107	$6,116	$6,055	$5,969	$5,924	$5,840	$6,490
Yes	Single	$6,225	$5,992	$5,726	$5,720	$5,783	$5,784	$5,622	$5,601	$5,523	$5,631
Yes	Married	$5,883	$5,701	$5,491	$5,486	$5,535	$5,535	$5,407	$5,391	$5,328	$5,421
500-999											
No	Single	$6,354	$6,170	$6,004	$5,984	$5,990	$5,935	$5,859	$5,818	$5,742	$6,334
No	Married	$6,004	$5,863	$5,734	$5,718	$5,723	$5,681	$5,622	$5,589	$5,529	$5,984
Yes	Single	$5,732	$5,572	$5,389	$5,384	$5,426	$5,426	$5,314	$5,298	$5,243	$5,332
Yes	Married	$5,494	$5,367	$5,221	$5,217	$5,250	$5,249	$5,160	$5,147	$5,102	$5,179
1000+											
No	Single	$6,088	$5,940	$5,810	$5,792	$5,793	$5,743	$5,687	$5,651	$5,587	$6,112
No	Married	$5,798	$5,684	$5,582	$5,568	$5,569	$5,530	$5,485	$5,457	$5,407	$5,814
Yes	Single	$5,396	$5,286	$5,160	$5,156	$5,183	$5,181	$5,104	$5,092	$5,053	$5,133
Yes	Married	$5,228	$5,139	$5,037	$5,034	$5,055	$5,053	$4,991	$4,982	$4,949	$5,020

Table 36: Annual income from a $100,000 investment into an annuity product: Gender = Female, State = Cardiac, With Transitions.

Annuity Income (With Transitions) - Female - Cardiac											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$6,666	$6,459	$6,304	$6,269	$6,222	$6,139	$6,087	$6,028	$5,924	$7,065
No	Married	$6,208	$6,057	$5,942	$5,917	$5,884	$5,822	$5,782	$5,738	$5,661	$6,484
Yes	Single	$4,955	$4,925	$4,891	$4,888	$4,885	$4,879	$4,861	$4,853	$4,836	$4,938
Yes	Married	$4,888	$4,863	$4,833	$4,830	$4,828	$4,822	$4,807	$4,800	$4,785	$4,874
500-999											
No	Single	$6,112	$5,971	$5,864	$5,841	$5,809	$5,751	$5,714	$5,673	$5,600	$6,370
No	Married	$5,799	$5,694	$5,612	$5,594	$5,571	$5,527	$5,498	$5,466	$5,410	$5,983
Yes	Single	$4,868	$4,843	$4,815	$4,812	$4,810	$4,804	$4,790	$4,783	$4,769	$4,855
Yes	Married	$4,813	$4,791	$4,766	$4,764	$4,762	$4,757	$4,744	$4,738	$4,726	$4,801
1000+											
No	Single	$5,940	$5,819	$5,727	$5,706	$5,680	$5,629	$5,597	$5,561	$5,498	$6,159
No	Married	$5,670	$5,578	$5,507	$5,491	$5,473	$5,432	$5,408	$5,379	$5,330	$5,829
Yes	Single	$4,820	$4,799	$4,774	$4,772	$4,770	$4,764	$4,752	$4,746	$4,733	$4,813
Yes	Married	$4,771	$4,752	$4,731	$4,729	$4,727	$4,722	$4,711	$4,706	$4,694	$4,765

Table 37: Annual income from a $100,000 investment into an annuity product: Gender = Female, State = Diabetes, With Transitions.

Annuity Income (With Transitions) - Female - diabetes

Home Ownership	Marital Status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	$6,575	$6,384	$6,222	$6,187	$6,160	$6,083	$6,045	$5,970	$5,892	$6,776
No	Married	$6,141	$6,001	$5,882	$5,857	$5,839	$5,780	$5,749	$5,696	$5,635	$6,287
Yes	Single	$5,132	$5,085	$5,020	$5,012	$5,000	$5,001	$4,981	$4,956	$4,936	$5,070
Yes	Married	$5,012	$4,974	$4,923	$4,917	$4,911	$4,909	$4,891	$4,873	$4,856	$4,963
500-999											
No	Single	$6,032	$5,905	$5,796	$5,772	$5,753	$5,702	$5,674	$5,624	$5,568	$6,163
No	Married	$5,741	$5,645	$5,562	$5,545	$5,532	$5,491	$5,468	$5,431	$5,387	$5,840
Yes	Single	$4,988	$4,951	$4,902	$4,897	$4,889	$4,888	$4,872	$4,853	$4,837	$4,943
Yes	Married	$4,898	$4,867	$4,828	$4,824	$4,819	$4,817	$4,802	$4,789	$4,775	$4,861
1000+											
No	Single	$5,869	$5,759	$5,667	$5,647	$5,633	$5,584	$5,559	$5,518	$5,468	$5,994
No	Married	$5,620	$5,535	$5,464	$5,450	$5,439	$5,401	$5,380	$5,349	$5,309	$5,715
Yes	Single	$4,898	$4,868	$4,831	$4,827	$4,821	$4,819	$4,805	$4,792	$4,777	$4,868
Yes	Married	$4,827	$4,802	$4,771	$4,768	$4,765	$4,762	$4,749	$4,739	$4,727	$4,803

Table 38: Annual income from a $100,000 investment into an annuity product: Gender = Female, State = Healthy, With Transitions.

Annuity Income (With Transitions) - Female - Healthy

Home Ownership	Marital Status	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
<499											
No	Single	$6,545	$6,345	$6,194	$6,162	$6,151	$6,056	$6,009	$5,949	$5,867	$6,795
No	Married	$6,121	$5,976	$5,864	$5,841	$5,832	$5,762	$5,726	$5,682	$5,620	$6,295
Yes	Single	$5,011	$4,977	$4,933	$4,930	$4,929	$4,925	$4,901	$4,892	$4,873	$4,968
Yes	Married	$4,936	$4,906	$4,868	$4,865	$4,865	$4,860	$4,840	$4,832	$4,816	$4,899
500-999											
No	Single	$5,994	$5,866	$5,766	$5,745	$5,736	$5,674	$5,642	$5,602	$5,545	$6,149
No	Married	$5,717	$5,620	$5,543	$5,528	$5,520	$5,473	$5,447	$5,417	$5,372	$5,830
Yes	Single	$4,910	$4,881	$4,846	$4,844	$4,843	$4,838	$4,819	$4,812	$4,796	$4,877
Yes	Married	$4,848	$4,823	$4,792	$4,790	$4,789	$4,785	$4,769	$4,762	$4,749	$4,820
1000+											
No	Single	$5,861	$5,747	$5,658	$5,639	$5,631	$5,575	$5,547	$5,511	$5,460	$6,004
No	Married	$5,614	$5,527	$5,458	$5,444	$5,437	$5,394	$5,372	$5,344	$5,303	$5,719
Yes	Single	$4,850	$4,826	$4,797	$4,794	$4,793	$4,788	$4,773	$4,766	$4,753	$4,828
Yes	Married	$4,796	$4,775	$4,749	$4,747	$4,746	$4,742	$4,729	$4,723	$4,711	$4,778

Table 39: Annual income from a $100,000 investment into an annuity product: Gender = Female, State = Mental Health, With Transitions.

Annuity Income (With Transitions) - Female - mentalHealth											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$6,531	$6,365	$6,215	$6,188	$6,157	$6,081	$6,027	$5,972	$5,890	$6,744
No	Married	$6,121	$5,998	$5,885	$5,865	$5,842	$5,785	$5,744	$5,703	$5,639	$6,274
Yes	Single	$5,075	$5,048	$4,996	$4,994	$4,981	$4,982	$4,951	$4,942	$4,920	$5,029
Yes	Married	$4,981	$4,956	$4,912	$4,910	$4,901	$4,901	$4,875	$4,867	$4,848	$4,942
500-999											
No	Single	$6,003	$5,892	$5,790	$5,772	$5,750	$5,699	$5,662	$5,624	$5,566	$6,141
No	Married	$5,728	$5,642	$5,563	$5,549	$5,533	$5,493	$5,464	$5,435	$5,389	$5,831
Yes	Single	$4,951	$4,927	$4,886	$4,885	$4,876	$4,875	$4,852	$4,844	$4,826	$4,916
Yes	Married	$4,877	$4,855	$4,821	$4,819	$4,813	$4,811	$4,792	$4,785	$4,770	$4,848
1000+											
No	Single	$5,859	$5,759	$5,670	$5,654	$5,637	$5,589	$5,557	$5,523	$5,472	$5,988
No	Married	$5,617	$5,539	$5,470	$5,457	$5,444	$5,406	$5,381	$5,354	$5,313	$5,714
Yes	Single	$4,880	$4,859	$4,826	$4,824	$4,817	$4,815	$4,796	$4,790	$4,774	$4,856
Yes	Married	$4,817	$4,798	$4,770	$4,768	$4,763	$4,761	$4,745	$4,739	$4,726	$4,798

Table 40: Annual income from a $100,000 investment into an annuity product: Gender = Female, State = Pain Medication, With Transitions.

Annuity Income (With Transitions) - Female - painMed											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$7,083	$6,884	$6,633	$6,682	$6,635	$6,463	$6,503	$6,499	$6,376	$7,433
No	Married	$6,526	$6,380	$6,195	$6,231	$6,197	$6,070	$6,098	$6,094	$6,002	$6,772
Yes	Single	$5,107	$5,070	$5,009	$5,021	$5,017	$4,996	$4,989	$4,990	$4,965	$5,074
Yes	Married	$5,008	$4,976	$4,925	$4,934	$4,931	$4,914	$4,907	$4,906	$4,886	$4,979
500-999											
No	Single	$6,458	$6,323	$6,140	$6,182	$6,147	$6,021	$6,057	$6,059	$5,970	$6,693
No	Married	$6,065	$5,962	$5,824	$5,855	$5,829	$5,734	$5,759	$5,759	$5,691	$6,234
Yes	Single	$4,989	$4,959	$4,909	$4,918	$4,916	$4,897	$4,892	$4,893	$4,873	$4,965
Yes	Married	$4,907	$4,881	$4,840	$4,847	$4,845	$4,830	$4,824	$4,824	$4,807	$4,887
1000+											
No	Single	$6,227	$6,110	$5,956	$5,989	$5,960	$5,852	$5,880	$5,879	$5,803	$6,430
No	Married	$5,890	$5,801	$5,684	$5,708	$5,686	$5,604	$5,624	$5,622	$5,562	$6,040
Yes	Single	$4,916	$4,890	$4,849	$4,857	$4,854	$4,837	$4,834	$4,834	$4,816	$4,901
Yes	Married	$4,846	$4,824	$4,789	$4,795	$4,792	$4,779	$4,775	$4,774	$4,759	$4,834

Table 41: Annual income from a $100,000 investment into an annuity product: Gender = Female, State = Parkinsons, With Transitions.

Annuity Income (With Transitions) - Female - parkinsons											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$6,734	$6,508	$6,316	$6,324	$6,284	$6,195	$6,115	$6,075	$5,972	$6,831
No	Married	$6,293	$6,123	$5,977	$5,983	$5,952	$5,885	$5,823	$5,792	$5,712	$6,363
Yes	Single	$5,093	$5,047	$4,990	$4,989	$4,990	$4,985	$4,953	$4,944	$4,921	$5,020
Yes	Married	$5,003	$4,963	$4,914	$4,913	$4,914	$4,909	$4,882	$4,874	$4,854	$4,941
500-999											
No	Single	$6,138	$5,989	$5,861	$5,863	$5,837	$5,777	$5,723	$5,694	$5,623	$6,213
No	Married	$5,841	$5,726	$5,626	$5,627	$5,607	$5,560	$5,518	$5,494	$5,438	$5,897
Yes	Single	$4,968	$4,931	$4,887	$4,885	$4,886	$4,881	$4,856	$4,849	$4,830	$4,914
Yes	Married	$4,895	$4,863	$4,825	$4,823	$4,825	$4,820	$4,799	$4,792	$4,776	$4,850
1000+											
No	Single	$5,947	$5,822	$5,716	$5,714	$5,693	$5,640	$5,597	$5,570	$5,509	$6,029
No	Married	$5,692	$5,595	$5,511	$5,509	$5,493	$5,451	$5,417	$5,395	$5,347	$5,755
Yes	Single	$4,892	$4,861	$4,825	$4,823	$4,824	$4,819	$4,799	$4,792	$4,777	$4,854
Yes	Married	$4,830	$4,804	$4,773	$4,771	$4,771	$4,767	$4,750	$4,744	$4,730	$4,799

Table 42: Annual income from a $100,000 investment into an annuity product: Gender = Male, State = Antithrombotic, With Transitions.

Annuity Income (With Transitions) - Male - antithrombotic											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$8,260	$7,880	$7,582	$7,459	$7,432	$7,269	$7,286	$7,118	$6,955	$8,737
No	Married	$7,189	$6,944	$6,753	$6,672	$6,656	$6,545	$6,557	$6,444	$6,336	$7,495
Yes	Single	$31,398	$23,556	$21,590	$21,009	$20,622	$19,160	$20,469	$16,969	$15,208	$48,127
Yes	Married	$20,062	$16,078	$15,029	$14,720	$14,510	$13,705	$14,422	$12,483	$11,474	$27,814
500-999											
No	Single	$7,254	$7,002	$6,805	$6,720	$6,703	$6,590	$6,602	$6,487	$6,375	$7,569
No	Married	$6,536	$6,367	$6,235	$6,178	$6,167	$6,088	$6,096	$6,016	$5,939	$6,746
Yes	Single	$19,996	$16,033	$14,994	$14,679	$14,472	$13,676	$14,386	$12,458	$11,453	$27,763
Yes	Married	$14,163	$11,949	$11,345	$11,163	$11,041	$10,568	$10,987	$9,839	$9,226	$18,218
1000+											
No	Single	$6,730	$6,541	$6,391	$6,326	$6,313	$6,226	$6,234	$6,146	$6,060	$6,966
No	Married	$6,183	$6,053	$5,950	$5,905	$5,897	$5,834	$5,839	$5,778	$5,717	$6,344
Yes	Single	$15,232	$12,714	$12,036	$11,826	$11,690	$11,162	$11,631	$10,343	$9,658	$19,940
Yes	Married	$11,480	$9,994	$9,580	$9,452	$9,368	$9,040	$9,329	$8,530	$8,095	$14,113

Table 43: Annual income from a $100,000 investment into an annuity product: Gender = Male, State = Cardiac, With Transitions.

Annuity Income (With Transitions) - Male - Cardiac											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$7,932	$7,669	$7,438	$7,272	$7,281	$7,076	$7,062	$6,954	$6,848	$8,387
No	Married	$6,961	$6,791	$6,639	$6,534	$6,538	$6,405	$6,396	$6,324	$6,252	$7,237
Yes	Single	$6,525	$6,397	$6,293	$6,249	$6,243	$6,154	$6,168	$6,093	$6,029	$6,643
Yes	Married	$6,142	$6,039	$5,957	$5,927	$5,921	$5,852	$5,866	$5,803	$5,751	$6,232
500-999											
No	Single	$7,042	$6,866	$6,707	$6,596	$6,601	$6,462	$6,452	$6,378	$6,302	$7,336
No	Married	$6,383	$6,265	$6,156	$6,083	$6,085	$5,991	$5,986	$5,934	$5,881	$6,569
Yes	Single	$6,152	$6,047	$5,966	$5,933	$5,928	$5,860	$5,873	$5,810	$5,758	$6,251
Yes	Married	$5,852	$5,767	$5,702	$5,679	$5,673	$5,620	$5,632	$5,579	$5,537	$5,931
1000+											
No	Single	$6,569	$6,435	$6,313	$6,229	$6,232	$6,126	$6,119	$6,062	$6,002	$6,785
No	Married	$6,065	$5,973	$5,887	$5,831	$5,832	$5,759	$5,754	$5,714	$5,671	$6,206
Yes	Single	$5,924	$5,834	$5,766	$5,739	$5,734	$5,678	$5,690	$5,635	$5,590	$6,013
Yes	Married	$5,672	$5,598	$5,544	$5,524	$5,519	$5,475	$5,485	$5,440	$5,403	$5,744

Table 44: Annual income from a $100,000 investment into an annuity product: Gender = Male, State = Diabetes, With Transitions.

Annuity Income (With Transitions) - Male - diabetes											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$7,636	$7,413	$7,134	$7,026	$7,002	$6,876	$6,839	$6,790	$6,634	$7,783
No	Married	$6,774	$6,628	$6,449	$6,379	$6,364	$6,277	$6,254	$6,218	$6,115	$6,875
Yes	Single	$6,940	$6,772	$6,620	$6,596	$6,575	$6,474	$6,500	$6,400	$6,298	$6,976
Yes	Married	$6,490	$6,348	$6,230	$6,213	$6,196	$6,115	$6,140	$6,052	$5,970	$6,538
500-999											
No	Single	$6,839	$6,688	$6,502	$6,428	$6,412	$6,323	$6,299	$6,263	$6,155	$6,948
No	Married	$6,254	$6,150	$6,027	$5,976	$5,966	$5,902	$5,887	$5,859	$5,786	$6,331
Yes	Single	$6,478	$6,337	$6,223	$6,202	$6,186	$6,108	$6,131	$6,045	$5,964	$6,541
Yes	Married	$6,121	$6,002	$5,913	$5,896	$5,884	$5,821	$5,842	$5,768	$5,703	$6,186
1000+											
No	Single	$6,423	$6,306	$6,165	$6,107	$6,095	$6,025	$6,007	$5,977	$5,894	$6,511
No	Married	$5,971	$5,889	$5,793	$5,752	$5,745	$5,693	$5,682	$5,658	$5,600	$6,035
Yes	Single	$6,194	$6,070	$5,978	$5,958	$5,946	$5,882	$5,902	$5,826	$5,758	$6,269
Yes	Married	$5,891	$5,787	$5,715	$5,699	$5,689	$5,637	$5,655	$5,591	$5,536	$5,962

Table 45: Annual income from a $100,000 investment into an annuity product: Gender = Male, State = Healthy, With Transitions.

Annuity Income (With Transitions) - Male - Healthy											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$7,716	$7,476	$7,163	$7,052	$7,023	$6,897	$6,879	$6,800	$6,668	$7,871
No	Married	$6,780	$6,630	$6,439	$6,368	$6,351	$6,267	$6,257	$6,203	$6,118	$6,884
Yes	Single	$6,842	$6,683	$6,534	$6,510	$6,490	$6,395	$6,424	$6,323	$6,236	$6,874
Yes	Married	$6,407	$6,273	$6,160	$6,143	$6,127	$6,051	$6,077	$5,991	$5,920	$6,449
500-999											
No	Single	$6,853	$6,696	$6,496	$6,421	$6,404	$6,316	$6,305	$6,250	$6,161	$6,965
No	Married	$6,240	$6,136	$6,008	$5,958	$5,947	$5,885	$5,879	$5,840	$5,779	$6,318
Yes	Single	$6,397	$6,265	$6,154	$6,134	$6,119	$6,046	$6,070	$5,985	$5,915	$6,454
Yes	Married	$6,055	$5,944	$5,859	$5,843	$5,831	$5,772	$5,793	$5,721	$5,664	$6,113
1000+											
No	Single	$6,418	$6,299	$6,150	$6,092	$6,080	$6,012	$6,003	$5,960	$5,892	$6,507
No	Married	$5,954	$5,872	$5,774	$5,734	$5,726	$5,676	$5,671	$5,640	$5,592	$6,018
Yes	Single	$6,126	$6,010	$5,922	$5,903	$5,891	$5,830	$5,851	$5,778	$5,718	$6,194
Yes	Married	$5,838	$5,741	$5,671	$5,657	$5,647	$5,598	$5,616	$5,554	$5,505	$5,902

Table 46: Annual income from a $100,000 investment into an annuity product: Gender = Male, State = Mental Health, With Transitions.

Annuity Income (With Transitions) - Male - mentalHealth											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$7,649	$7,422	$7,120	$7,037	$7,006	$6,864	$6,860	$6,774	$6,649	$7,705
No	Married	$6,789	$6,640	$6,446	$6,391	$6,372	$6,274	$6,272	$6,212	$6,128	$6,829
Yes	Single	$8,291	$7,953	$7,484	$7,599	$7,510	$7,185	$7,310	$7,087	$6,920	$7,543
Yes	Married	$7,431	$7,174	$6,839	$6,920	$6,855	$6,619	$6,712	$6,540	$6,413	$6,931
500-999											
No	Single	$6,828	$6,676	$6,480	$6,420	$6,401	$6,304	$6,300	$6,241	$6,155	$6,886
No	Married	$6,250	$6,146	$6,015	$5,974	$5,962	$5,892	$5,890	$5,848	$5,788	$6,293
Yes	Single	$7,196	$6,969	$6,687	$6,742	$6,690	$6,492	$6,569	$6,417	$6,303	$6,832
Yes	Married	$6,630	$6,451	$6,244	$6,283	$6,244	$6,096	$6,155	$6,036	$5,947	$6,389
1000+											
No	Single	$6,402	$6,287	$6,140	$6,092	$6,078	$6,004	$6,000	$5,954	$5,888	$6,459
No	Married	$5,960	$5,879	$5,778	$5,744	$5,735	$5,681	$5,679	$5,645	$5,597	$6,002
Yes	Single	$6,623	$6,449	$6,256	$6,284	$6,249	$6,111	$6,165	$6,050	$5,963	$6,432
Yes	Married	$6,198	$6,061	$5,915	$5,935	$5,908	$5,804	$5,846	$5,754	$5,685	$6,077

Table 47: Annual income from a $100,000 investment into an annuity product: Gender = Male, State = Pain Medication, With Transitions.

Annuity Income (With Transitions) - Male - painMed											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$8,263	$7,967	$7,619	$7,522	$7,520	$7,318	$7,320	$7,239	$7,100	$8,510
No	Married	$7,220	$7,026	$6,795	$6,733	$6,732	$6,596	$6,598	$6,543	$6,448	$7,376
Yes	Single	$7,465	$7,239	$6,993	$6,992	$6,984	$6,841	$6,883	$6,793	$6,677	$7,508
Yes	Married	$6,850	$6,670	$6,487	$6,487	$6,478	$6,370	$6,405	$6,327	$6,236	$6,899
500-999											
No	Single	$7,270	$7,071	$6,838	$6,771	$6,770	$6,631	$6,632	$6,575	$6,479	$7,439
No	Married	$6,564	$6,429	$6,269	$6,224	$6,223	$6,127	$6,128	$6,088	$6,020	$6,675
Yes	Single	$6,828	$6,650	$6,473	$6,469	$6,461	$6,355	$6,389	$6,312	$6,221	$6,891
Yes	Married	$6,364	$6,220	$6,086	$6,083	$6,076	$5,994	$6,022	$5,956	$5,884	$6,425
1000+											
No	Single	$6,734	$6,585	$6,410	$6,357	$6,356	$6,250	$6,251	$6,206	$6,131	$6,864
No	Married	$6,198	$6,094	$5,971	$5,935	$5,934	$5,859	$5,859	$5,827	$5,773	$6,286
Yes	Single	$6,440	$6,292	$6,154	$6,147	$6,140	$6,057	$6,085	$6,016	$5,942	$6,512
Yes	Married	$6,063	$5,943	$5,838	$5,832	$5,826	$5,761	$5,784	$5,726	$5,667	$6,129

Table 48: Annual income from a $100,000 investment into an annuity product: Gender = Male, State = Parkinson's, With Transitions.

Annuity Income (With Transitions) - Male - parkinsons											
Home Ownership	**Marital Status**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
<499											
No	Single	$7,714	$7,480	$7,200	$7,105	$7,072	$6,957	$6,887	$6,848	$6,711	$7,774
No	Married	$6,888	$6,729	$6,539	$6,474	$6,451	$6,371	$6,321	$6,293	$6,198	$6,929
Yes	Single	$7,163	$6,968	$6,824	$6,793	$6,774	$6,670	$6,709	$6,577	$6,474	$7,277
Yes	Married	$6,688	$6,518	$6,403	$6,380	$6,363	$6,278	$6,314	$6,199	$6,112	$6,804
500-999											
No	Single	$6,893	$6,734	$6,548	$6,480	$6,459	$6,376	$6,334	$6,300	$6,207	$6,957
No	Married	$6,326	$6,214	$6,084	$6,036	$6,022	$5,961	$5,931	$5,907	$5,839	$6,371
Yes	Single	$6,681	$6,512	$6,400	$6,373	$6,358	$6,275	$6,309	$6,196	$6,110	$6,810
Yes	Married	$6,291	$6,145	$6,056	$6,035	$6,022	$5,955	$5,984	$5,888	$5,817	$6,412
1000+											
No	Single	$6,469	$6,347	$6,204	$6,150	$6,135	$6,068	$6,038	$6,009	$5,936	$6,528
No	Married	$6,028	$5,939	$5,837	$5,799	$5,788	$5,739	$5,717	$5,695	$5,642	$6,069
Yes	Single	$6,375	$6,224	$6,131	$6,107	$6,094	$6,025	$6,055	$5,955	$5,881	$6,507
Yes	Married	$6,038	$5,910	$5,836	$5,817	$5,806	$5,750	$5,775	$5,692	$5,631	$6,157