# Mortality Beliefs and Saving Decisions: The Role of Personal Experiences<sup>\*</sup>

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#### Abstract

This paper is the first to non-experimentally establish a causal relationship between households' mortality beliefs and subsequent saving and consumption decisions. Motivated by prior literature on the effect of personal experiences on individuals' expectation formation, I exploit the death of a close friend as an exogenous shock to the salience of mortality of a household. Using data from a large household panel, I find that the death of a close friend induces a significant reduction in saving rate of 1.1 percentage points that grows to 1.7 percentage points over the following 6 years. I show that the incorporation of personal experiences in mortality beliefs can be explained by the canonical consumption life-cycle model augmented by the experience-based learning model. The saving response to the shock strongly depends on households' age, emotional involvement, risk aversion, and decays over time. Overall, this paper provides novel insights into *whether* and *how* mortality beliefs are incorporated into households' financial planning.

*Keywords:* Household finance, Mortality beliefs, Belief formation, Personal experiences, Household saving, Life-cycle model *JEL Codes:* D14, D15, G41, G51

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# 1 Introduction

Mortality beliefs are a critical component of the canonical life-cycle model of consumption and saving. In these models, agents that underestimate their life expectancy undersave and experience significant shortcomings in retirement income. In practice, poverty in old age is a pressing issue in many developed countries. According to a recent Congressional Research Service report, a staggering 11.1 percent of people aged 80 or older in the US live in poverty (Li & Dalaker, 2021). This is the highest number among all other age groups. As miscalibrations in longevity expectations have an enormous impact on households' welfare, it is crucial to understand *whether* and *how* individuals incorporate mortality beliefs in their saving decisions.

Even though the theoretical relationship between longevity expectations and the saving rate is well established, there is little empirical research showing that individuals in fact consider mortality beliefs in their financial decision-making. It is difficult to demonstrate a causal link between mortality salience and saving decisions both due to a lack of non-experimental data as well as endogeneity concerns. Mortality beliefs are typically correlated with the socioeconomic status of an individual, which itself is highly correlated with financial decision making. Similarly, health shocks tend to both entail a lowered life expectancy as well as out-of-pocket expenses. In this paper, I address these issues by utilizing a plausible exogenous shock to an individual's mortality beliefs and demonstrate that more pessimistic mortality beliefs translate into lower saving rates. I exploit the self reported death of a close friend as a negative shock to mortality beliefs. This idea is founded in the literature on how personal experiences shape economic expectations (e.g. Malmendier & Nagel, 2011). Intuitively, personal experiences matter because individuals overweight the probability of an event happening if they can more easily recall similar events. Hence, one should become more pessimistic about one's own longevity if a close friend recently died.

Furthermore, there is little evidence on *how* households incorporate personal experiences into the mortality belief formation process. In this paper, I formalize the intuition that personal experiences make rare events salient for the belief formation process by introducing the experience-based learning (EBL) model of Malmendier, Pouzo, and Vanasco (2020) in the context of a life-cycle consumption model. Based on the empirical predictions generated by the model, I validate that the shock affects saving decisions through the channel of mortality beliefs. Furthermore, I can rule out alternative channels like pure Bayesian updating. After calibrating the model, I quantify the impact of the shock on mortality beliefs and the decay of the effect over time using SMM. Overall, I am the first, to my knowledge, to establish a non-experimental causal link between households' mortality beliefs and saving decisions. On top of that, I provide non-survey evidence on how personal experiences in the domain of mortality affect financial decision making.

In this paper, I use a long-running representative panel covering the Australian population to exploit the death of a close friend as an exogenous shock on the mortality beliefs of an individual. I link this shock to both an individual's mortality beliefs and her consumption-saving allocation. Due to the nature of the panel data, I can compare, within person, the saving rate of an individual before and after experiencing the death of a close friend. The data set is unique in that it collects detailed information on a household's saving and consumption behavior, a plethora of information on the socio-economic status and attitudes of a household as well as whether a close friend died in the previous year. I find that the death of a close friend on average reduces the saving rate by 1.1 percentage points directly after the shock. This effect grows to 1.7 percentage points over the following years. Considering the non-material nature of the shock, the effect size is considerable. Breaking down the changes into consumption subcategories reveals that the impact is not driven by sudden increases in medical expenditure but by expenditure on leisure related items. Moreover, I rule out that the effect stems from bequests, drastic life changes, or deteriorating health conditions. On top of that, the data allows me to explicitly link the death of a close friend to a subsequent significant decrease in subjective longevity expectations reported by the households. Furthermore, I strengthen this link by establishing that the effect on the saving rate is driven by households that rely on savings for their retirement and individuals with a weak bequest motive. These analyses demonstrates that the exogenous shock works through the intended channel.

Next, I explore how the personal experience of a close friend dying is incorporated into mortality beliefs. I augment the classic life-cycle model by the experience-based learning (EBL) to account for the subjective component of mortality beliefs due to the personal experience. Based on this theoretical framework, I derive several testable implications and test them empirically. First, the reduction in saving rate in response to the shock is 1.4 percentage points for younger individuals compared to 0.9 percentage points for older individuals. This is consistent with the idea that each new experience makes up a larger proportion of the set of relevant experiences for younger agents and thereby they are more strongly affected by them. In the periods following the initial shock, the effect size grows to be two times as large for younger versus older individuals. Second, the EBL model predicts that the effect should gradually decay as long as there are no new shocks. Intuitively, the experience fades out of memory over time. Indeed, I find in my empirical data that the initial drop in saving rate monotonically decreases over the six years following the initial shock. After 3 years, the effect is roughly half of the initial shock. Third, a prediction that arises naturally from the life-cycle consumption model is that a reduction in perceived survival rate has a more pronounced effect on the saving rate of individuals with low risk aversion. I find that low risk aversion households reduce their saving rate almost twice as much as high risk aversion individuals following the death of a close friend (2.5 pp versus 1.4 pp). Fourth, Malmendier (2021) argues that the emotional strength of the experience crucially determines whether it is considered in the decision making process. I proxy for the emotional reaction with the self-reported character trait of emotional coldness and discover that individuals that rank high on this trait do not exhibit any reduction in saving rate.

Finally, I fit the theoretical model to the empirical results. I find that depending on the level of risk aversion the survival rate is reduced by 1.4 for a CRRA risk aversion coefficient of 1 to 17.1 percentage points for a CRRA risk aversion coefficient of 5. The reduction in survival rate decays to zero over the following 6 years. Furthermore, I estimate the associated decay parameter from the EBL model using SMM. My parameter estimate range from 1.7 to 2.1. This is comparable to the estimates of Malmendier and Nagel (2011) who estimate a  $\lambda$  of around 1.4 to 1.9. Overall, these results suggest a causal link between mortality beliefs and households' saving decisions. An exogenous shock to mortality beliefs induces a significant reduction in saving behavior. Moreover, I provide evidence that experience-based learning plays an important role in the mortality belief formation process.

This paper adds to the academic literature exploring the effect of mortality beliefs on saving and investment decisions. This literature goes back to Hamermesh (1985) who elicits subjective survival probabilities and discusses the implications for household saving models. Since then, several papers attempt to link mortality beliefs to saving decisions (Hurd et al., 2004; Puri & Robinson, 2007; De Nardi et al., 2010; Post & Hanewald, 2013; Jarnebrant & Myrseth, 2013; Spaenjers & Spira, 2015). In particular, Spaenjers and Spira (2015) attempt to rule out endogeneity concerns by instrumenting an individual's subjective survival probabilities with the death of their parents. My paper goes a step further by removing associations of hereditary illnesses and bequest issues from the equation. The death of a close friend should not be correlated with ones own genetic history as well as should not result in significant windfall gains due to bequests. Furthermore, most of the aforementioned papers utilize health and retirement studies and therefore focus on older individuals. Conversely, my paper covers a representative sample of the Australian population, which includes households at all stages of life. This facilitates the generalizability of my results and provides additional insights into younger households for whose lifetime utility these financial decisions matter the most.<sup>1</sup>

More broadly, I contribute to the literature investigating the role of personal experiences in financial decision making and expectation formation. In general, these studies find that individuals overweight personal experiences in the expectation formation process. This has been shown in a variety of contexts like IPOs (Kaustia & Knüpfer, 2008), investments in 401(k)s (Choi et al., 2009), financial risk taking (Malmendier & Nagel, 2011; Knüpfer et al., 2017; Bernile et al., 2017), inflation expectations (Malmendier & Nagel, 2016), household leverage (Kalda, 2020), house price expectations (Kuchler & Zafar, 2019; Bailey et al., 2018), and unemployment rate expectations (Kuchler & Zafar, 2019). My paper adds to this by showing that in the realm of mortality expectations a similar effect can be observed. Experiencing the loss of a close friend makes people more pessimistic about their own longevity and subsequently translates into altered financial decision making.

<sup>&</sup>lt;sup>1</sup>There is also recent concurrent work by Kárpáti (2022) who exploits genetic testing to establish a causal link between objective mortality beliefs and a wide range of financial outcomes in a representative Dutch dataset.

This paper is closely related to the seminal work by Heimer, Myrseth, and Schoenle (2019). They argue that young individuals underestimate survival whereas older individuals overestimate survival. The authors hypothesize that younger individuals overweight rare events due to them being salient. Hence, the salience of death distorts mortality beliefs and subsequently crucially affects optimal household decision-making. My paper contributes direct evidence that mortality salience affects mortality beliefs and thereby financial decision-making. Furthermore, my findings might provide a possible link between personal experiences and the overweighting of rare events for the young. Younger individuals are more likely in relative terms to die due to such rare events. Hence, their friends learn about these events and subsequently overweight the likelihood of such an event happening to themselves.

The paper is structured as follows. Section 2 outlines the canonical life-cycle model and derives the importance of survival probabilities in that context. Furthermore, I adapt the experiencebased learning model and demonstrate how the personal experience affects mortality beliefs over time. Section 3 describes the data and introduces the identification strategy. Section 4 shows the results regarding the empirical relationship between mortality salience, mortality beliefs, and saving behavior. Section 5 explores the channel through which mortality beliefs affect saving decisions. Section 6 links the estimation results back to the theoretical model introduced in section 2. Section 7 concludes.

# 2 Theoretical Framework

#### 2.1 Life-cycle Consumption Model

I set up a classic life-cycle model to demonstrate the importance of mortality expectations for the consumption and saving decision (e.g. Deaton, 1991; Hubbard et al., 1995). For details regarding the model setup refer to appendix B1. In the model, a representative household maximizes its expected lifetime utility. The household receives stochastic income each period and decides how much to allocate to consumption and the remainder is allocated to saving. I assume that there is only one asset with a risk-free rate of R. Furthermore, each household lives a maximum of T periods and is assumed to have a power utility function. This gives rise to the following maximization problem:

$$\max \mathbb{E}[\sum_{t=1}^{T} \beta^{t-1} (\prod_{j=0}^{t-2} s_j) u(c_t)]$$
(1)

where  $c_t$  is a household's consumption,  $\beta$  a time discount factor, and  $s_j$  the probability of surviving to period j. One can rewrite this problem in recursive form as a Bellman equation:

$$\nu_t(m_t) = \max_{c_t} \ u(c_t) + \beta s_{t+1} \mathbb{E}[(p_{t+1}/p_t)^{1-\rho} \nu_{t+1}(m_{t+1})]$$
(2)

where  $m_t$  is the available resources that could be potentially used for consumption,  $p_t$  is the permanent labor income in period t, and  $\rho$  is the coefficient of relative risk aversion of a power utility function. Taking the derivative gives rise to the following first order condition:

$$0 = u'(c_t) - \beta s_{t+1} \mathbb{E}[R(p_{t+1}/p_t)^{-\rho} \nu_{t+1}(m_{t+1})]$$
(3)

Solving for  $c_t$  yields the following optimal consumption in t:

$$c_t^* = (\beta s_{t+1})^{-1/\rho} (\mathbb{E}[\cdot])^{-1/\rho}$$
(4)

Even though there is no analytical solution to this problem, it is straightforward to see from the optimal consumption equation that a decrease in the survival probability leads to an increase in consumption and thereby a reduction in saving rate. I argue in this paper that the death of a close friend increases the salience of death for an individual. Subsequently, she becomes more pessimistic about her mortality beliefs, which translates into a lower survival rate  $s_{t+1}$ . Thus,  $c_t^*$  increases and mechanically the saving rate decreases. Intuitively, the agent does not defer her consumption as much if there is a certain probability that she will not survive to the next period. Largely following Cocco, Gomes, and Maenhout (2005), I calibrate this model to the Australian panel and solve it numerically. Table 17 lists the exact parameter values. For details regarding the model setup and solution refer to appendix B.

#### [Insert Figure 1 about here.]

Figure 1 shows the numerical solutions for the above introduced model after calibrating it to my data. The upper left panel demonstrates an average household's wealth accumulation until retirement and the subsequent depletion of these savings. Similarly, the upper right panel illustrates the average consumption at each age. Again, one can observe a hump-shaped line. However, the increase and subsequent decrease is a lot less steep, consistent with households smoothing their consumption over the life-cycle. Next, the lower left panel illustrates the average saving rate which switches from positive to negative after reaching retirement. Finally, the lower right panel illustrates the probability of surviving to the next period at each age. Each graph shows the solution for (1) a household that has objective mortality beliefs taken from the Australian Bureau of Statistics in black and (2) a household that has relatively speaking 5 percent more pessimistic mortality beliefs in red. Although the pessimistic household has a negative outlook on its survival, it faces objective probabilities of actually surviving. Comparing the solution for the baseline household and the more pessimistic household illustrates that unsurprisingly the latter accumulates a lot less wealth during her working life. The consumption path demonstrates the importance of mortality beliefs for optimal saving behavior. The more pessimistic household overconsumes until retirement but in retirement the agent is confronted with her considerably lower capital stock which leads to a consumption gap during that period. Comparing the areas between the graphs before and after they intersect, additionally, suggests significant utility losses for the pessimistic household.

In conclusion, mortality beliefs clearly have important implications for an agent's saving behavior in the context of a life-cycle model. An agent who is more pessimistic about her survival has an unambiguously lower saving rate all else equal. However, there is little empirical evidence that causally links mortality beliefs to saving decisions. This paper addresses the gap. In the next part, I propose how a shock to mortality beliefs induced by the death of a close friend translates into a change in survival rates in the context of an experienced-based learning model.

#### 2.2 Mortality Belief Formation

I adapt the experience-based learning model of Malmendier et al. (2020) to put a more rigorous structure on how the death of a close friend affects an agent's mortality beliefs. The agent experiences the death of a close friend which translates into a negative shock to her mortality beliefs. In the context of the life-cycle model, this means a reduction in the perceived survival rate in that period. In each period, the agent weighs these past periods depending on how long they have been ago and forms the expectation about her survival rate for the current period. I use the weighting function proposed by Malmendier et al. (2020):

$$w(k,\lambda,age) = \frac{(age+1-k)^{\lambda}}{\sum_{k,=0}^{age} (age+1-k')^{\lambda}}$$
(5)

where w is the weight an agent at *age* assigns to the personal experience experienced k periods ago. The parameter  $\lambda$  determines the weight of more recent compared to less recent experiences. As agents rarely experience the death of a close friend, mortality beliefs will become gradually more optimistic after the initial negative shock as long as  $\lambda > 0$ . Hence, one should observe an initially strong drop in the saving rate which in the following periods is attenuated.

#### [Insert Figure 2 about here.]

Figure 2 displays the average wealth, consumption, saving rate, and perceived survival probabilities of an agent that receives a negative shock of 10 percent at the age of 41 to her survival rate. This shock decays according to equation (5) assuming a  $\lambda$  of 1.5 over the following 10 years. The figure zooms in on the ages 39 to 49. The drop in survival rate results in a slight increase in consumption and a reduction in survival rate. This effect decays over time and after five years the effect has almost vanished. I expect to observe a similar pattern in the data if the death of a close friend would act as a personal experience and induce a shock to mortality beliefs. The shock to mortality beliefs initially strongly reduces the saving rate. This effect should attenuate over the subsequent years.

# 3 Data and Methodology

#### 3.1 Data

I employ data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. HILDA is a household panel study surveying around 17,000 Australians each year beginning in 2001. Table 1 shows summary statistics for a variety of variables of interest. As the HILDA panel aims to survey a representative sample of the Australian population, it is not surprising that the sample consists of 50 percent women, the average age lies around 37, and the average income equals 75,426 Australian dollar with the median only being roughly 60,000 Australian dollar.

#### [Insert Table 1 about here.]

My main dependent variable is an individual's saving behavior. I use three measures to elicit an individual's savings decision. First, participants are asked "Which of the following statements comes closest to describing your (and your family's) savings habits?". The predefined answer range from "don't save: usually spend more than income" to "save regularly by putting money aside each *month*". Second, participants are asked about their saving horizon with possible answers ranging from "the next week" to "more than 10 years ahead". Finally, I also directly calculate the savings rate from the consumption stated by households in the survey. Beginning with the fifth wave of the panel, individuals are asked about their annual expenditure covering a wide range of items<sup>2</sup>. These items include for example groceries, alcohol, clothing, pharmaceuticals, and many others. For a comprehensive list refer to Table 19 in the Appendix. Following Dynan, Skinner, and Zeldes (2004), I calculate the saving rate as one minus the sum all of these expenditures divided by the total aftertax income reported by the household. Furthermore, I exclude any household-year observation where the household received any windfall payments to ensure that the results are not driven by received inheritances. Finally, I winsorize at the 3 percent level to ensure that outliers are not driving the results. Yet, the results do not depend on the winsorized percentage. The average saving rate is 54 percent, which is significantly higher than official statistics by the Australian Bureau of Statistics. This is due to consumption elicited by the panel only covers non-durable consumption and even there might not comprehensively cover all subareas. However, there is little reason to believe that my calculated savings rate is systematically biased across individuals<sup>3</sup>. Furthermore, figure 3 shows the average saving rate by age. The graph displays the typical hump-shaped age

<sup>&</sup>lt;sup>2</sup>If several members of the household provided answers, the responses were averaged by HILDA.

 $<sup>^{3}</sup>$ In Table 16, I regress the saving rate on various demographics. All the variables behave as expected irrespective of the aggregation method.

profile (e.g. Guvenen, 2007; Aguiar & Hurst, 2013) which further suggests that the aggregated consumption represents a sensible proxy for a household's saving rate.

#### [Insert Figure 3 about here.]

My main independent variable of interest is the death of a close friend dummy. It equals 1 if the participant states that a close friend died within the last 12 months before the survey. Unconditionally, 11 percent of respondents experienced such an event in the previous year. This seemingly large percentage is in line with the percentage elicited by the Australian Bureau of Statistics for the General Social Survey (Liu et al., 2019). The perceived life expectancy is measured by the question *"How likely do you think it is that you will live to be 75 or more?"* where people aged older than 65 are asked how likely it is that they live for 10 more years. The answers range from *"Very likely"* to *"Very unlikely"* on a four point ordinal scale. On average, individuals are optimistic about their life expectancy with around 45 percent of respondents stating that it is unlikely or very unlikely that they are going to live to 75.

Furthermore, I utilize two variables for sample splits. First, I elicit an individual's risk aversion using the question "Are you generally a person who is willing to take risks or are you unwilling to take risks?". The answers range from 0 to 10 where I rescale the answers such that a higher value indicates a higher level of risk aversion. On average, the distribution is centered around the value of 5 with a standard deviation of around 2.5. Second, I obtain a person's emotional coldness by employing the question "How well do the following words describe you? - Cold". The answers to this question range from 1 to 7 where a higher value indicates that the characteristic describes an individual well. Obviously, most individuals are reluctant to identify themselves as emotionally cold such that the median value is only 2. Nevertheless, there are several participants reporting high levels of emotional coldness.

For all regressions on household level, I exclude households where it is likely that financial decision-making is done independently by household members, but the consumption behavior is still aggregated on household level. These include for example siblings living together or shared flats. If there is a couple living in the household, I require both partners to report the death of a close friend as the financial decision-making is not easily attributable to one of the two. Next, I describe the identification strategy I employ in this paper.

#### **3.2** Identification

My identification strategy is based on the idea that the death of a close friend represents an exogenous negative shock to an individual's mortality beliefs. This is rooted in the literature on how personal experiences affect an individual's beliefs in a wide range of economic contexts (e.g.

Malmendier & Nagel, 2011; Kuchler & Zafar, 2019). At the same time, using the death of a close friend as a shock to the mortality beliefs of an individual has two advantages over previous attempts that utilize the death of a family member (e.g. Spaenjers & Spira, 2015). First, the death of a non-relative should not affect the financial situation of an individual. It is rare that a deceased individual bequests a meaningful amount of wealth to a friend rather than her family members. Second, the death of parents or siblings often contains information about an individual's own hereditary health risks. Hence, the effect should not be driven by a response to a signal about one's own health. It could be argued that the death of a close friend represents a signal about the health consequences about an individual's own lifestyle. However, I will show in later parts that the effect is most pronounced for demographics where this is highly unlikely.

Furthermore, using panel data allows me to abstract from personal characteristics that have been shown to affect the financial decision making of an individual like income (Imbens et al., 2001; Dynan et al., 2004) or financial literacy (Calvet et al., 2007; Van Rooij et al., 2011). Hence, I employ person or household fixed effects as well as age fixed effects to elicit the within person change in saving behavior following the shock to mortality beliefs. Thus, I estimate the following regression model:

$$S_{it} = \beta F D_{i,t} + \gamma_t + \delta_i + \epsilon_{it} \tag{6}$$

where  $S_{it}$  represents the saving rate of either an individual or a household depending on the respective unit of observation in year t. FD signifies that the unit of observation reports the death of a close friend in the previous year. Finally,  $\gamma_t$  are age fixed effects and  $\delta_i$  either person or household fixed effects. Similarly, I also elicit the long-term effect of the shock on the saving rate:

$$S_{it} = \beta F D_{i,t+1,T} + \gamma_t + \delta_i + \epsilon_{it} \tag{7}$$

where  $FD_{i,t+1,T}$  is an indicator variable equal to 1 for each period after the death of a close friend was reported excluding the event period. Hence, the  $\beta$  captures the absolute change in saving rate after the shock compared to all periods before the shock including the shock period.

#### 4 Empirical Results

#### 4.1 Effect of a close friend's death on the saving decision

First, I establish that the exogenous shock to mortality beliefs indeed has an impact on the saving behavior of a household. Table 3 reports the results of regressing various measures of saving on a dummy variable indicating that the death of a close friend occurred within the last year. All regressions include both person or household as well as age fixed effects. Furthermore, I cluster standard errors by person or household to account for auto-correlation. Crucial for these regressions is the timing of the death of a friend dummy. When I regress saving habit on the death of a friend dummy, I lag the variable as saving habit represents a backward looking persistent behavior. Thus, I avoid that the event, namely the death of a friend, and the self-reported saving behavior overlap. Conversely, the saving horizon is a forward looking variable describing future behavior. Hence, there is no need to lag the death of a friend dummy as the shock to the salience of death and the described behavior are sufficiently separated.

#### [Insert Table 3 about here.]

Column 1 of table 3 shows the results of regressing the saving rate on the death of a close friend dummy. As I include both household and age fixed effects, the coefficient of the *Death friend* variable represents the change in saving rate in the year a close friend dies compared to the change in saving rate of untreated individuals net of the age-saving profile. On average, the death of a close friend reduces the saving rate by 1.1 percentage points. This coefficient is highly significant at the 1 percent level. I do not control for potentially time-varying income in this regression specification as income is the denominator of the dependent variable. To address potential concerns associated with staggered differences-in-differences estimators as raised by Baker, Larcker, and Wang (2022), I implement the estimator proposed by Sun and Abraham (2021) and the stacked regression estimator as in Cengiz, Dube, Lindner, and Zipperer (2019). Furthermore, I also run the test on the subset of households that experience a positive change in income in the year a close friend died. This should ensure that the findings are not driven by a reduction in income due to the shock. Table 18 shows the results of these analyses. Clearly, these alternative specifications barely change the coefficient estimates.

Columns 2 and 3 display the coefficients of regressing the *Saving Habit* variable on the death of a close friend in the previous year. On average, the death of a close friend reduces the *Saving Habit* variable by 0.02, both controlling for income and without. This is statistically significant at the 5 percent level. Similarly, columns 4 and 5 show the results of regressing the *Saving Horizon* variable on the death of a close friend dummy. The effect size is comparable to the preceding estimations. The death of a close friend reduces the *Saving Horizon* variable on average by 0.02. Yet, this coefficient is marginally not statistically significant at the 10 percent level with a t-statistic of 1.59. The estimated coefficients do not change when controlling for income<sup>4</sup>. Considering the stickiness of these ordinal variables and that they are only included every two years in the survey, it is not surprising that the coefficient magnitude is comparably small. This might also explain the low statistical significance of the *Saving Habit* variable. Nevertheless, these findings support the hypothesis that the death of a close friend induces a negative shock to mortality beliefs which

 $<sup>{}^{4}</sup>$ I run OLS regressions for better interpretability of the results. The online appendix shows that the findings also hold for ordered logit regressions.

subsequently results in an increase in consumption and reduction in saving. Moreover, taking into consideration the possibility that the death of a close friend also has a negative impact on mortality beliefs in the subsequent periods, it is likely that the coefficients of these analyses are underestimating the overall effect. In the next section, I explore the long-term impact of the shock to mortality beliefs on the saving rate to test for this.

In conclusion, these findings provide evidence that the death of a close friend has a significant impact on the saving behavior of individuals and households. Moreover, this effect is observable for the saving rate as well as for the stated saving behavior. Interestingly, there is also evidence that individuals actually shorten their saving horizon in response to this shock to mortality beliefs. Overall, this suggests that the death of a close friend represents a negative exogenous shock to mortality beliefs and that a shift in mortality beliefs has an impact on saving behavior. Yet, it is not possible to draw definite conclusions regarding the underlying mechanism at this point. It is for example possible that the sorrow induced by this shock triggers coping mechanisms that result in excessive consumption. Hence, in the next section I explore the long-term impact of the shock on a household's saving decision.

#### 4.2 Long-term effect

Next, I explore the long-term effect of a close friend's death on a household's saving rate. For that purpose, I construct an indicator variable that equals 1 for every year after an individual reports for the first time that a close friend died and 0 else. If a household consists of a couple, I require that both individuals have experienced the death of a close friend in the past for the indicator variable to equal 1. As I include both household and age fixed effects, this variable compares the saving rate before and including the death of a friend to the saving rate after that event. I report the results in table 4. Furthermore, I explore which components of consumption increase most following the death of a close friend. Hence, I cluster the various subcategories into three groups: leisure related expenditure, expenditure on necessities, and health and insurance related expenditure. For details refer to table 19. On top of that, I also split the sample at roughly median working age to examine potential differences across age groups.

#### [Insert Table 4 about here.]

Panel A of table 4 reports the results for the pooled sample. Column 1 shows that after the shock to mortality beliefs the saving rate is on average 1.7 percentage points lower compared to before the shock. This effect is highly significant at the 1 percent level. Comparing this coefficient with the initial 1 percent drop in saving rate from the previous analysis suggests that the negative shock to mortality beliefs persists in the following periods to a certain degree. Yet, it also indicates that the effect likely weakens over time. I explore this in more detail in part 5.2. Furthermore, this

is evidence against the idea that the death of a close friend simply triggers an emotional reaction that is then treated by excessive consumption. It is unlikely that the effect would persist for several years.

Panel B and C display similar results for both the younger and older half of the sample. The death of a close friend reduces the subsequent saving rate for the younger than 45 year old by on average 2.5 percentage points and by 1.3 percentage points for the older than 45 year old. Both coefficients are significant at the 1 percent level. Moreover, the difference between both coefficients is significant at the 5 percent level. Interestingly, the effect of mortality beliefs on saving decisions is a lot stronger for younger individuals. This finding is consistent with the idea that younger individuals have collected less experience. Hence, a new experience receives a larger weight in the decision making process. I further explore this idea in section 5.1. Columns 2 to 4 break the increase in consumption driven by the shock to mortality beliefs down into the three aforementioned components. The regressions show that the death of a close friend increases both expenditure on leisure and on necessities by 0.6 percentage points. This is significant at the 1 percent level. Conversely, the expenditure on health and insurance related items only increases by 0.2 percentage points, which is still significant at the 1 percent level. Overall, these results indicate that the long-term effect is not driven by a sudden shift in concern about one's health and an associated need to visit the doctor excessively.

However, the pooled regressions hide considerable heterogeneity. The death of a close friend increases the expenditure on leisure of the younger half by 1.1 percentage points, whereas the coefficient drops to 0.3 percentage points for the older half. Yet, both coefficients are significant at the 1 percent level. Conversely, the consumption of necessities increases by 0.8 percentage points both for the younger individuals as well as the older individuals with both coefficients being significant at the 5 percent level. For the older individuals this represents the largest increase in consumption following a shock to mortality beliefs. Partly, the difference might simply represent a shift in what constitutes fun expenditure. Expenditure on leisure mainly contains alcohol, cigarettes and meals eaten out. More mature individuals might not be as much inclined to go out partying to increase consumption compared to younger individuals. This is supported by figure 4 which shows a breakdown of the relative expenditure on the three subcategories for both age groups. The relative expenditure on necessities is similar for both age groups. However, some of the relative expenditure on leisure of the older half of the sample is replaced by expenditure on health and insurance products. Finally, the death of a close friend subsequently increases the expenditure on health for younger individuals by a marginal 0.1 percentage points and for older individuals by 0.2 percentage points. In relative terms, these coefficients are comparable as older individuals are spending 50 percent more on health and insurance compared to younger individuals (cf. figure 4).

In conclusion, these findings support the idea that the salience of death has a long-term impact on one's mortality beliefs. It contradicts the notion that the drop in saving rate is simply caused by mechanisms to deal with grief like shopping or excessive alcohol consumption. It is possible that one could observe such behavior immediately following the death of a close friend. However, it is unlikely that such behavior persists for several years across the whole sample. Furthermore, the results show that the effect is not driven by a response to the signal to one's own health the death of a close friend represents. Instead, especially younger individuals increase consumption of goods that are adverse to their health like tobacco or alcohol. On top of that, it is also at odds with individuals expecting higher medical expenses in the future as this would result in an increase in precautionary savings (De Nardi et al., 2010).

#### 4.3 Effect of a friend's death on life expectancy

The necessary condition for the death of a close friend being a plausible shock is that it in fact has a negative impact on mortality beliefs. The HILDA panel allows me to explicitly test for this link. I utilize the question "How likely is it that you are going to live to 75?". The question is asked only three times with each being 4 years apart. Yet, it is possible to conduct some basic analyses to demonstrate that the death of a close friend actually affects an individual's life expectancy. Furthermore, I can replicate the finding of previous papers that mortality beliefs have a strong impact on saving decisions (e.g. Heimer et al., 2019). Figure 5 plots the distribution of answers to the life expectancy question by age bins. Overall, individuals are optimistic about their survival probability until the age of 75. This is justified as 75 is significantly lower than the current life expectancy in Australia. Comparing the distribution of answers for the 20 to 35 year old with the answers of the 45 to 60 year old might provide some evidence for a similar pattern as reported by Heimer et al. (2019). Younger individuals also appear to be slightly pessimistic about their survival rates compared to their older counterparts. Conversely, the above 75 year old individuals might be slightly optimistic about their survival as a significant portion is reporting that it is "Very Likely" or "Likely" to live to 75. Yet, the exact interpretation of the findings depends on the perception of the question by participants.

#### [Insert Figure 5 about here.]

Columns 1 and 2 of table 5 display the results of regressing the likelihood to live to 75 on the death of a close friend either in the same period or in the previous period. I run OLS regressions with individual and age fixed effects. Standard errors are clustered at the individual level. Thus, I elicit the within person change in stated survival probability due to the exogenous shock. Column 1 shows that the death of a close friend has a significant impact on an individual's mortality beliefs. On average, the shock reduces the stated likelihood to live to 75 category by 0.027. This coefficient is statistically significant at the 5 percent level. In addition, column 2 indicates that there is still a negative impact on next period's stated life expectancy. However, the effect size is halved and

the statistical significance is low. Yet, considering the limited power of these tests due to the small sample size and the inclusion of individual fixed effects the reaction is considerable. Overall, this analysis demonstrates that such a shock to the salience of death has a significant negative effect on life expectancy. These findings provide further evidence that the previous results that a friend's death translates into less saving and more consumption is driven by changes in mortality beliefs.

#### [Insert Table 5 about here.]

Next, I establish that mortality beliefs have a significant impact on saving behavior. Previous literature suggests that mortality beliefs are correlated with the saving rate (e.g. Post & Hanewald, 2013). The challenge with these results is that both mortality beliefs and saving rate are strongly correlated with observable and unobservable factors like income, health, and financial literacy. I go one step further by including person and age fixed effects when regressing the saving rate on life expectancy. Thus, I explore the within person change in saving behavior following a change in mortality beliefs. Columns 3 and 4 of table 5 exhibit the results of regressing the saving rate on the likelihood to live to 75 variable. On average, going from one category to a higher category increases the saving rate by 0.5 percentage points. This is statistically significant at the 5 percent level. Similarly, a positive change in the previous period increases next period's saving rate by 0.5 percentage points as well. This coefficient is still statistically significant at the 10 percent level. Yet, this is not conclusive evidence that mortality beliefs causally affect saving behavior. It would be for example possible that an individual falls ill which both affects mortality beliefs negatively and might induce increased spending on health care related expenditure. This is the reason I exploit in the previous section the exogenous shock to mortality beliefs induced by the death of a close friend.

To further solidify he link between the shock to mortality beliefs and saving decisions, I exploit the fact that many Australians mainly rely on state pensions as source of income for retirement. Conversely, if a household receives a negative shock to mortality beliefs and mostly relies on its savings for the retirement period, the resulting reduction of the saving rate should be more pronounced. In table 6, I perform three sample splits to test this hypothesis. Unfortunately, the questions, I rely on for the sample splits, are only asked to 45 year olds and older that have not yet reached retirement. Hence, I can only draw conclusions for the older half of the sample.

#### [Insert Table 6 about here.]

Columns 1 and 2 show that only if households report saving and investments as a part of their retirement income, they significantly reduce their saving rate in response to a close friend dying. On average, the saving rate is reduced by 1.6 percentage points which is statistically significant at the 5 percent level. This finding becomes even more pronounced when focusing on households that report savings and investments as their *main* source of retirement income. On average, these

households reduce their saving rate by 3.9 percentage points following the death of a close friend which is three times the coefficient of the overall sample. This effect is statistically significant at the 5 percent level. Finally, in columns 5 and 6, I group households according to state pensions being part of their retirement income. As expected, households that report to rely on a state pension in retirement exhibit a reduced response to the shock to mortality beliefs with regards to saving compared to households not relying on state pensions. In general, these results suggest that the death of a close friend indeed serves as a shock to mortality beliefs.

On top of that, an agent's bequest motive should play a significant role in her saving decision if indeed the death of a close friend represents a negative shock to mortality beliefs. If an agent considers bequests to be a part of her utility function, the reduction in saving rate in response to the shock should be less pronounced. Thus, I proxy for the bequest motive with the parenthood status of households.

#### [Insert Table 7 about here.]

Table 7 shows the results of regressing the saving rate on the death of a close friend indicator variable depending on whether households have children. Columns 1 and 2 demonstrate that childless households reduce, on average, their saving rate by 2.3 percentage points which is highly statistically significant at the 1 percent level. Conversely, parents reduce their saving rate by only 0.7 percentage point. This indicates that households consider bequest motives in their response to a close friend dying which suggests that mortality beliefs are negatively affected by the shock. Yet, the reduced effect size might be caused by parents having less leeway in financial matters as they have to provide for their children. Hence, columns 3 and 4 present the findings for the sample of parents depending on whether their child is still part of the household or not. Indeed, parents having their child living with them do not react to the shock. Households that do not having a child living with them reduce the saving rate by 1.2 percentage points. This effect is statistically significant at the 1 percent level. However, the coefficient is half the coefficient of the childless households whereas childless households only have a 10 percent higher saving rate. Hence, households seem to consider bequests when confronted with the death of a close friend even though the effect on the saving rate is not fully mitigated by having a child to bequeath to. In conclusion, the findings regarding retirement income and bequest motive further support the notion that the exogenous shock works through the intended channel of mortality beliefs becoming more pessimistic.

In principle, there are two channels through which the death of a close friend might negatively affect mortality expectations. First, consistent with the literature on the effect of personal experiences on expectation formation (e.g. Malmendier & Nagel, 2016; Kuchler & Zafar, 2019), the agent overweights the likelihood of the rare event happening due to its salience. Thus, she irrationally forms too pessimistic mortality expectations. Second, the death of a friend might be a credible signal about an individual's survival probabilities as her lifestyle and the lifestyle of the dead friend

are correlated. Hence, the agent rationally updates her expectations due to the signal about the unobserved consequences of her own lifestyle. At this point, it is not possible to cleanly distinguish between these two channels. However, I derive predictions that arise from the EBL model within the life-cycle consumption model in the next part. These results show that a health signal based explanation is unlikely and heavily favor a salience based explanation.

# 5 Testable implications of the model

After establishing a significant link between mortality beliefs and saving decisions, I turn to the question in which way the salience of death affects mortality beliefs and subsequently saving decisions. The model introduced in section 2 generates several unique testable implications how the shock to mortality beliefs should affect the saving rate. I empirically test these predictions to validate the hypothesized channel of experience-based learning. First, younger individuals should be more strongly affected by the shock than older individuals. Second, the effect size should decay over time. Third, the life cycle consumption model predicts a stronger impact of mortality beliefs for less risk-averse individuals. Last, the strength of the emotion associated with the shock matters for the magnitude of the effect. In the following parts, I derive these predictions in more detail and test them empirically.

#### 5.1 Effect by age

Following the argument of Malmendier (2021), the experience of the death of a close friend should have a more pronounced effect on the beliefs of younger individuals. Intuitively, younger individuals have experienced less relevant events such that a new event constitutes a larger weight in their set of experiences and thereby in their expectation formation process. Subsequently, the change in saving behavior should be more drastic for younger individuals. To test this hypothesis, I split the sample along the age of 45, which roughly represents the median working age in my sample. I repeat the baseline regression for each of the two subsamples separately. Table 8 shows the results of the analysis.

[Insert Table 8 about here.]

Columns 1 and 2 display the findings for the *Saving Rate* variable. The death of a close friend reduces on average the saving rate of the younger subsample by 1.4 percentage points. Conversely, the effect for the older half of the sample is -0.9 percentage points. Both coefficients are statistically significant at the 5 percent level. Considering that both subsamples have a similar average saving rate, the coefficient suggests that younger individuals are roughly 50 percent more affected by the shock to mortality beliefs compared to older individuals. This is strong evidence that indeed such a shock makes up a larger portion of the set of experiences of younger individuals which in turn means a larger effect on the saving rate.

Next, columns 3 and 4 show the effect of the shock to mortality beliefs on the *Saving Habit* variable for both subsamples. On average, the death of a close friend reduces the reported saving habit category by 0.05 for the younger households. This effect is statistically significant at the 5 percent level. Contrarily, the impact on the saving rate of the above 45 year old is negligible with a coefficient of 0.014 and no statistical significance. Similarly, columns 5 and 6 exhibit the influence of the shock on an individual's saving horizon. The shock to mortality beliefs decreases the reported saving horizon category by around 0.035 which is statistically significant at the 10 percent level. This effect is four times as large compared to the older subsample. For these participants, the death of a close friend reduces the reported saving horizon category by only 0.009 which is statistically insignificant.

The difference in effect size between the older and younger individuals cannot be explained by the difference in average saving behavior. The mean for all three saving proxies is similar making the relative effect size comparable. Overall, the effect of such a personal experience appears to be three to four times as big for the younger half of the sample compared to the older half. This is in line with the idea that younger individuals should react more strongly to a new experience as it constitutes a larger part of their set of experiences. Similarly, column 1 in table 4 shows that this difference in effect size is not only observable in the same period but also the following years. On average, the exogenous shock reduces the saving rate by 2.5 percentage points for the younger sample half. This is roughly double the coefficient compared to the older half of the sample. Moreover, figure 6 splits the sample into four age groups and displays on the left the immediate effect of a close friend's death on the saving rate and on the right the effect in the following periods. The bars indicate 95 percent confidence intervals. Clearly, the death of a close friend has the largest impact on the younger than 30 year old. Considering the long-term impact, the effect appears to be similar in magnitude across the other age groups. Again, this is in line with the argument that younger individuals have a lot less relevant experiences in the mortality domain, which results in a relatively higher weight of the new experience in the expectation formation process.

Furthermore, these findings indicate that it is not the information about one's life expectancy associated with the death of a close friend but rather the stimulus provided by the experience that leads to an updating of beliefs. Assuming that most individuals have friends that are in a similar age range as themselves, the informational content of the death of an older individual is a lot higher compared to younger individuals. The deaths of younger individuals are mostly due to accidents or suicide whereas the deaths of older individuals are mostly due to diseases (c.f. table 20) which are partly attributable to lifestyle choices. Hence, on average older individuals should update their beliefs more strongly than younger individuals if they were responding to an informational signal.

#### 5.2 Effect decay

Next, I explore the dynamic effect of the exogenous shock on a household's saving rate. The adapted version of the experience-based learning (EBL) model by Malmendier et al. (2020) predicts a decay in the effect size over time. In contrast to Malmendier et al. (2020), mortality is a domain with few relevant experiences. Hence, an agent experiences the death of a close friend only sporadically and typically lacks any further relevant experiences. Hence, the synaptic connections weaken and die over time as they are not activated anymore which in turn translates into an effect decay over time. Intuitively, these experiences fade out of memory. To test this hypothesis, I estimate the following regression model:

$$S_{it} = \sum_{e=-6}^{e=6} \beta_e F D_{ite} + \gamma_i \times \tau_t + \epsilon_{it}$$
(8)

where e is the time relative to the event of a close friend dying for household i in year t.  $\gamma_i$ are age fixed effects and  $\tau_t$  represents year fixed effects. Each of the  $\beta$  represents then the average reduction or increase in the saving rate compared to the observations outside the event window. The implicit assumption here is that all periods outside of the event window are not affected by the event, which seems to be empirically the case. In case that a household experiences several shocks in close temporal proximity, I reset, in the spirit of the EBL model, the event time to zero. The new shock makes the issue salient again. I only include working age households into this analysis to avoid biasing the results due to households entering the workforce or entering retirement. Table 9 reports the results of this analysis.

#### [Insert Table 9 about here.]

Column 1 shows the results of regressing the saving rate on a set of dummies indicating each of the 6 periods preceding and following the event of a close friend dying. On average, the death of a close friend reduces the saving rate in the same period by 5.7 percentage points compared to all periods outside of the event window. This effect is reduced to 3.3 percentage points in the two following periods. Subsequently, this drops to 2.5 percentage points. All of these coefficients are highly significant at the 1 percent level. Finally, the coefficients for the periods 5 and 6 are only -1.2 and -0.7 percentage points and statistically insignificant. Figure 7 plots the coefficients of column 1. Overall, these results confirm that the effect of the large initial shock decays over time. This is in line with the hypothesis that individuals put a larger weight on more recent experiences compared to more distant ones. However, as households do not face any new relevant experiences the effect on the saving rate declines over time.

[Insert Figure 7 about here.]

The results also exhibit a slight effect in the year preceding the death of a close friend. On average, households appear to reduce their consumption by 2.1 percentage points. However, comparing the coefficient with the post period shows that the effect is small as the 4 years following the event indicate a larger effect size. Furthermore, it is in the context of mortality salience not surprising to observe an anticipatory effect as most individuals do not die suddenly but succumb to illness. Columns 2 and 3 display analogous findings when shortening the event window around the death of a close friend. This illustrates that the results do not depend on the chosen event window as there is no reaction previous to the event and the effect decays to zero after around four to five years. Based on the coefficients of the above analysis, it is possible to estimate the decay parameter  $\lambda$  from the weighting function introduced in part 2.2. I conduct this analysis in part 6. Comparing the estimated parameter with previous estimates in the literature reveals a striking similarity. In addition, slow effect decay is inconsistent with pure Bayesian updating. If individuals would simply update their beliefs in response to new information, one would observe an instantaneous non-reverting change in the saving rate.

#### 5.3 Risk aversion

As described earlier, the optimal consumption in period t is given by:

$$c_t^* = (\beta s_{t+1})^{-1/\rho} (\mathbb{E}[\cdot])^{-1/\rho}$$
(4)

One parameter that crucially determines the size of the effect of a shock to mortality beliefs on consumption is the risk aversion  $\rho$ . Everything else equal, households with higher risk aversion should increase their consumption more. Intuitively, low risk aversion households react less to the increased uncertainty surrounding their own survival. I use the question "On a scale from 0 to 10, are you generally a person who is willing to take risks or are you unwilling to take risks?" to elicit an individual's risk aversion. Next, I rescale the variable such that a high value indicates a high level of risk aversion. Finally, I split the sample into a high and a low risk aversion group. For each of these groups I separately run fixed effects regressions eliciting both the short-term and long-term impact of a friend's death on a household's saving decisions.

#### [Insert Table 10 about here.]

Columns 1 and 2 in table 10 show that a negative change in mortality beliefs reduces the saving rate on average by 1.4 percentage points for the high risk aversion households. This coefficient is almost two times as big for the low risk aversion households. Yet, both coefficients are highly significant at the 1 percent level. Similarly, the long term impact on the saving rate for the former group is 1.2 percentage points, whereas it increases to 2.2 percentage points for the latter. The statistical significance for the long-term effect of the high risk aversion individuals drops to the 10 percent level.

Overall, these results are in line with households optimizing their lifetime utility given a subjective adjustment of beliefs. High risk aversion households react significantly less to a change in the perceived survival rate compared to low risk aversion households. These findings lend further support for the importance of mortality beliefs in the canonical life-cycle model. Furthermore, the results strengthen the causal relationship between mortality beliefs and saving and consumption decisions.

#### 5.4 Depth of Emotion

According to modern neuroscience, more emotional events are better retained in memory (e.g. LaBar & Cabeza, 2006). Moreover, the strength of the emotional reaction determines how easily the memory is accessed. In my context, the model then predicts a stronger influence of the death of a close friend on mortality beliefs and the subsequent saving decision for individuals experiencing a more emotionally arousing event. Even though I cannot observe the size of the shock to mortality beliefs, I can find a proxy for the likely magnitude of the emotional reaction to that shock. I proxy for how strongly an individual is hit by the emotional shock by using the character trait "coldness". Individuals are regularly asked "On a scale from 1 to 7, how well does the following word describe you? - Cold". This question is asked every four waves, so I replace missing observations with the value of the most recent non-missing answer. Naturally, most individuals do describe themselves as rather warm. Hence, I split the sample not along the middle value but in a group reporting a higher value and a group reporting a lower value than 3.

#### [Insert Table 11 about here.]

Table 11 shows the effect of the death of a close friend on the saving rate for each group separately. Columns 1 and 2 display the results of regressing the saving rate on a dummy that equals 1 if a close friend died that period and zero otherwise. On average, the death of a close friend reduces the saving rate by 1.5 percentage points for the households that report being emotionally warm. This is statistically significant at the 1 percent level. Conversely, the "colder" households do not seem to react at all to the death of a close friend with an increase in the saving rate of 0.3 percentage points statistically indistinguishable from zero. Columns 3 and 4 report how the mortality shock affects the saving rate in the following periods for the not cold and cold households. The death of a close friend reduces the saving rate in the following periods. This effect is highly statistically significant at the 1 percent level. Again, the effect on the "colder" individuals is negligible. The saving rate is on average 0.3 percentage points lower with a t-statistic of 0.18.

Overall, these findings are strong evidence that the effect of experiences in the belief formation process requires a strong emotional reaction to that shock. This is in line with the argument made by Malmendier (2021) that personal experiences affect the expectation formation process by forming new synapses between neurons which makes these issues more salient to the decision-maker. Thus, this analysis corroborates the hypothesis that the death of a close friend represents a negative shock to mortality beliefs which then translates into more consumption and a lower saving rate. These results further support the idea that the shock affects mortality beliefs through the accessibility of personal experiences rather than through information. If the death of a close friend would provide a signal about one's own health which then results in an updating of beliefs there would likely be no difference in reaction between the two groups. This finding is inconsistent with pure Bayesian updating.

#### 5.5 Additional Robustness Checks

#### 5.5.1 Drastic Life Changes

I conduct additional analyses to rule out that drastic life choices are driving the results. Some alternative explanations could be brought forward how the death of a close friend does not directly affect the saving rate through increased survival pessimism but indirectly through a different mechanism. Yet, all of these explanations are also based on the notion that mortality beliefs are becoming more pessimistic and not necessarily inconsistent with the initial hypotheses.

#### [Insert Table 12 about here.]

First, the psychology literature asserts that mortality salience changes the timing of conceiving a child. Specifically, individuals that face a mortality salience shock perceive the ideal point of time to bear a child to be earlier (Wisman & Goldenberg, 2005; Fritsche et al., 2007). If individuals in my sample had an increased probability of getting a child following the mortality salience shock, it might mechanically increase consumption and thereby reduce the saving rate. To test for this channel, I simply regress a dummy variable that indicates a child birth in the previous year on the death of a close friend dummy lagged by 1 and 2 periods to account for the 9 months a pregnancy takes. Column 1 and 2 in table 12 demonstrate that the death of a close friend does not increase the likelihood to conceive a child. If anything, it reduces the probability of such an event, even though the economic significance of the coefficient is negligible. Second, the death of a close friend could lead to a drastic change in priorities in ones life. One could imagine that somebody quits her well-paying job to pursue a more fulfilling career. To address this issue, in columns 3 to 4 in table 12 I regress a dummy indicating a change in occupation on the death of a friend dummy. In columns 3, I regress on the same period change whereas in columns 4 the death of friend dummy is lagged. The results show that there does not seem to be neither an immediate nor a delayed reaction concerning an individual's job situation. Last, an individual might feel inclined to reduce her working hours in response to the death of a close friend to enjoy more free time. Thus in columns 5 and 6, I regress an individual's weekly hours worked on the death of a close friend dummy. However, the hours worked only increase on average by 0.06 following this shock which is both economically as well as statistically negligible.

In conclusion, there is no evidence for an indirect channel through which the death of a close friend induces a reduction in the saving rate. The shock to the salience of death neither leads to an increase in childbearing nor to significant changes to one's professional life. This analysis strengthens the idea that the shock to mortality beliefs has a direct effect on the consumption and saving decisions of a household.

#### 5.5.2 Health Shocks

Another remaining concern might be that the death of a close friend induces a deterioration in both physical or mental health. Indeed, Liu et al. (2019) find that the death of a close friend leads to a significant reduction in an individual's health and well-being. Even though, Table 4 already demonstrates that the overall reduction in saving rate can only partially be explained by an increase in health related expenditure, I repeat the main analyses while controlling for changes in both general as well as mental health. I utilize the well established SF-36 score which elicits an individual's health on a variety of dimensions. The rescaled scores range from 0 to 1 where a 1 indicates the best health possible. In addition, I also employ the subcategory mental health score as the death of a close friend might seriously impact one's psychological well-being. Finally, I average these scores on a household level.

#### [Insert Table 13 about here.]

Table 13 displays the results of regressing the saving rate on the death of a close friend indicator variable while controlling for the general and mental health. Columns 1 and 2 demonstrate that indeed an agent's health has a highly significant impact on her saving rate. On average, increasing the SF-36 general health score by one point (scaled to 0.01) increases the saving rate by 0.03 percentage points. Similarly, increasing the SF-36 mental health score by one point (scaled to 0.01) increases the saving rate by 0.047 percentage points. However, controlling for household health has no impact on the reduction in saving rate caused by the death of a close friend. The shock to mortality beliefs still decreases the saving rate by around 1.1 percentage points which statistically significant at the 1 percent level. Similarly, controlling for health does not mitigate the long-term effect of the shock on the saving rate. Columns 3 and 4 show that the health controls actually lead, on average, to a 3.6 percentage points reduction in saving rate following the death of a close friend. This is highly significant at the 1 percent level. Finally, columns 5 and 6 display the findings of

running the regressions of column 1 and 2 but only including households that experience a nonnegative change to their health following the death of a close friend. Again, there is no impact on the reduction in survival rate observable.

Overall, these results suggest that the reduction in saving rate in response to the death of a close friend are not caused by a deterioration in health in response to the shock. This further supports the notion that indeed the death of a close friend serves as a negative shock to an individual's mortality beliefs which in turn decreases his saving rate.

#### 5.5.3 Demographics

I perform various sample splits along the households' socioeconomic backgrounds to further explore how individuals are affected by the death of a close friend. These demographics include gender, education, financial literacy, religion, and urban versus rural inhabitants. As I have to perform these analyses on a household level, I aggregate couples depending on the demographic variable. For the gender, I simply take the first respondent in the survey. For education and financial literacy, I take the maximum achieved of both partners. Finally, I require both members of the household to be religious.

#### [Insert Table 14 about here.]

Table 14 reports the findings for the sample splits. Overall, I find little differences across these dimensions. One demographic that seems to induce differing reaction is an university degree. Compared to the baseline, there seems to be slightly larger effect size for the households holding an university degree. On average, the saving rate of university households is around 17 percent higher than for households without an university degree, whereas the effect size increased by 70 percent. Gender and financial literacy do not seem to have any differing impact on the results. Furthermore, neither religion nor living in a rural area affects the effect size considering that both non-religious as well as urban participants have a slightly higher average saving rate. Finally, individuals also report how long ago the close friend died. Curiously, there is an excessive probability of reporting that the death occurred within the last three months compared to the nine months before that. This suggests that participants either have trouble recalling the exact time of death or remembering the death if the incidence happened too long ago. Splitting the sample along this dimensions reveals a slightly larger effect for the less recent deaths. This finding is in line with both individuals being more likely to recall the death of a closer friend as well as having more time to adjust their consumption.

In conclusion, the socioeconomic background of the households does not seem to play a significant role in explaining the effect size. The only demographics that make a large difference are the theoretically founded ones discussed in chapter 5.1 to 5.4 like age, risk aversion, and emotional coldness. This finding is additional evidence that the life-cycle model of consumption and saving augmented by the experienced learning model explains the households' reaction to the shock to mortality beliefs well.

# 6 Fitting the Model to the Empirical Results

In a final step, I link the empirical results back to the theoretical model. There are two parameters of interest I cannot observe in the data: the actual reduction in survival rate induced by the shock and the decay parameter  $\lambda$ . However, using the model set up in part 2, I can back out the implied drop in survival rate consistent with the observed impact on the saving rate. Furthermore, based on the coefficients of the dynamic effect around the event estimated in part 5.2, it is possible to estimate the  $\lambda$  that is consistent with the observed decay in effect size.

First, I estimate the implied reduction in survival rate associated with the estimated coefficients in table 9. For that purpose, I minimize the difference between the relative reduction in saving rate estimated in that table and the relative reduction in saving rate given a reduction in survival rate in the life-cycle model simulations.

$$\min_{\Delta s_{e+1}} |\Delta S_e(\Delta s_{e+1}) - \Delta \hat{S}_e|$$
(9)

where  $\Delta \hat{S}_e$  is the relative reduction in saving rate estimated in table 9 for event time e and  $\Delta S_e(\Delta s_{e+1})$  is the relative reduction in saving rate given the reduction in survival rate  $\Delta s_{e+1}$  implied by model simulations, where  $s_{e+1}$  is the probability of surviving to period e + 1. I have to make two assumptions to conduct this analysis. First, I assume that in the baseline model all agents hold objective mortality beliefs. That means they act according to the survival rates taken from the Australian Bureau of Statistics. This is reasonable as previous research has shown that, on average, individual's longevity expectations are in line with actual survival patterns (Smith et al., 2001). Second, the subjective reduction in survival rate depends on the age an individual experiences the shock. However, I can only estimate the average effect across ages due to data limitations. Hence, for fitting the empirical results to the model, I assume that the death of a close friend occurs at roughly the average age the shock happens in the data which is 49. These two assumptions are necessary to put some structure on the estimation problem.

In a second step, I estimate the decay parameter using the implied reduction in survival rates. For details refer to appendix B3. First, I divide the estimated reductions in survival rate by the reduction in survival rate in period 0. Thereby, I calculate the implied weight of the initial shock in the following periods under the assumption that the initial shock receives 100 percent of the weight in period 0. Next, I calculate the weights for a list of possible  $\lambda$  values given by the model of Malmendier (2021):

$$w(k,\lambda,e) = \frac{(e+1-k)^{\lambda}}{\sum_{k'=0}^{e} (e+1-k')^{\lambda}}$$
(10)

Finally, I compute the squared difference between the implied weights by the empirical results and the theoretical weights.

$$\min_{\lambda} (\mathbf{w}(k,\lambda,e) - \hat{\mathbf{w}}(k,e))'(\mathbf{w}(k,\lambda,e) - \hat{\mathbf{w}}(k,e)) \quad \forall \ k = e \in [0,7]$$
(11)

where  $\hat{\mathbf{w}}$  is the vector of weights of the k-periods ago event from the relative reduction in  $\Delta s_{e+1}$  estimated from formula (9) and  $\mathbf{w}$  is the vector of weights implied by the above formula for a given  $\lambda$ . The minimum of the vector of squared differences provides the the  $\lambda$  value that fits the model closest to the empirical results. I can then compare the estimated  $\lambda$  with the  $\lambda$  estimated by Malmendier and Nagel (2011).

#### [Insert Table 15 about here.]

Table 15 displays the relative reduction in survival rate implied by the reduction in saving rate for various reasonable levels of risk aversion. Furthermore, the final row shows the associated decay parameter  $\lambda$ . Comparing the implied reduction across columns confirms the predictions from the model. Individuals with higher risk aversion react less to the same reduction in survival rate compared to low risk aversion individuals. For example, the relative drop in saving rate of around 0.11 in period 0 estimated earlier implies a relative reduction in survival rate of 1.4 percent for an individual with a risk aversion value of 1 whereas this rises to 17.1 percent for individuals with a  $\rho$ equal to 5. Similarly, in the next period this drops to a relative reduction of 0.8 percent compared to a relative reduction of 10.1 percent. Especially, the reductions in survival rate estimated for the lower levels of risk aversion appear to be in a reasonable range. On top of that, the empirical literature estimating the coefficient of relative risk aversion suggests values around 1 to 3 (e.g. Chetty, 2006). Independent of the exact level of impact of the shock to mortality beliefs, the implied decay parameter is similar. It varies between 1.7 and 2.1. This is in the range of the estimates of Malmendier and Nagel (2011) which lie between 1.3 and 1.9. It is likely that the structure of the experience drives the small difference. In the paper by Malmendier and Nagel (2011), the household experiences stock returns continuously over her lifetime. Yet in my context, most households only experience one shock that subsequently fades out of memory. Hence, it is reasonable to believe that the impact of the experiences decays faster.

These results closely link the theoretical framework to the empirical results. My estimates for the decay parameter  $\lambda$  are very similar to estimates in the literature. Overall, this strengthens the notion that the personal experience of losing a close friend acts as an exogenous shock to an agent's mortality beliefs. More specifically, I corroborate the findings of Malmendier and Nagel (2011) regarding the role of personal experiences in the expectation formation process in a vastly different domain.

### 7 Conclusion

My paper exploits an exogenous shock to the salience of death to causally link mortality beliefs to a household's saving decisions. I show that the death of a close friend has a significant negative impact on both life expectancy as well as a household's saving rate. The impact persists over several years and slowly declines over time. Furthermore, I introduce the experience-based learning model (Malmendier et al., 2020) into a canonical life-cycle model of consumption. Consistent with model predictions, younger, less risk-averse, and emotionally warm individuals exhibit a more pronounced reaction to the shock to mortality beliefs. Based on the coefficients of a dynamic regression around the event, I estimate the by the model implied reduction in survival rate and the associated decline parameter  $\lambda$  which proves to be in line with estimates from previous papers. The overall effect cannot be explained by adverse health outcomes or drastic lifestyle changes.

It is crucial to understand whether and how subjective mortality beliefs affect the financial planning of households as miscalibrations can lead to large lifetime utility losses due to undersaving for retirement. My results suggest that individuals do in fact consider mortality beliefs in their consumption-saving decisions apart from possible covariates like health, financial literacy, or wealth. Furthermore, the impact of the experience of a close friend dying is best understood through the lens of an experience-based learning model.

My results have important implications for both household finance as well as more generally for how economic expectations are formed. From a household finance point of view, my findings indicate that subjective mortality beliefs are an important component when evaluating the empirical fit of life-cycle models. Taking survival rates as purely exogenous parameters might severely distort model outcomes. Moreover, my results contribute new evidence to the importance of personal experiences in the expectation formation process. My findings are in accordance with the neuroscientific foundations for experience-based learning proposed by Malmendier (2021). Individuals overweight recent shocks to longevity expectations in their financial decision-making and subsequently overadjust their saving rate. Over time, this effect readjusts to the pre-shock level. The empirical findings are inconsistent with rational belief updating.

# References

- Aguiar, M., & Hurst, E. (2013). Deconstructing life cycle expenditure. Journal of Political Economy, 121(3), 437–492.
- Bailey, M., Cao, R., Kuchler, T., & Stroebel, J. (2018). The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy*, 126(6), 2224–2276.
- Baker, A. C., Larcker, D. F., & Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2), 370–395.
- Bernile, G., Bhagwat, V., & Rau, P. R. (2017). What doesn't kill you will only make you more risk-loving: Early-life disasters and ceo behavior. *The Journal of Finance*, 72(1), 167–206.
- Calvet, L. E., Campbell, J. Y., & Sodini, P. (2007). Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy*, 115(5), 707–747.
- Carroll, C. D., Kaufman, A. M., Kazil, J. L., Palmer, N. M., & White, M. N. (2018). The Econ-ARK and HARK: Open Source Tools for Computational Economics. In Fatih Akici, David Lippa, Dillon Niederhut, & M. Pacer (Eds.), *Proceedings of the 17th Python in Science Conference* (p. 25 - 30). doi: 10.25080/Majora-4af1f417-004
- Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. The Quarterly Journal of Economics, 134(3), 1405–1454.
- Chetty, R. (2006). A new method of estimating risk aversion. *American Economic Review*, 96(5), 1821–1834.
- Choi, J. J., Laibson, D., Madrian, B. C., & Metrick, A. (2009). Reinforcement learning and savings behavior. The Journal of Finance, 64(6), 2515–2534.
- Cocco, J. F., Gomes, F. J., & Maenhout, P. J. (2005). Consumption and portfolio choice over the life cycle. The Review of Financial Studies, 18(2), 491–533.
- Deaton, A. (1991). Saving and liquidity constraints. *Econometrica*, 59(5), 1221–1248.
- De Nardi, M., French, E., & Jones, J. B. (2010). Why do the elderly save? the role of medical expenses. *Journal of Political Economy*, 118(1), 39–75.
- Dynan, K. E., Skinner, J., & Zeldes, S. P. (2004). Do the rich save more? Journal of Political Economy, 112(2), 397–444.
- Fritsche, I., Jonas, E., Fischer, P., Koranyi, N., Berger, N., & Fleischmann, B. (2007). Mortality salience and the desire for offspring. *Journal of Experimental Social Psychology*, 43(5), 753– 762.
- Guvenen, F. (2007). Learning your earning: Are labor income shocks really very persistent? American Economic Review, 97(3), 687–712.
- Hamermesh, D. S. (1985). Expectations, life expectancy, and economic behavior. The Quarterly Journal of Economics, 100(2), 389–408.

- Heimer, R. Z., Myrseth, K. O. R., & Schoenle, R. S. (2019). Yolo: Mortality beliefs and household finance puzzles. *The Journal of Finance*, 74(6), 2957–2996.
- Hubbard, R. G., Skinner, J., & Zeldes, S. P. (1995). Precautionary saving and social insurance. Journal of Political Economy, 103(2), 360–399.
- Hurd, M. D., Smith, J. P., & Zissimopoulos, J. M. (2004). The effects of subjective survival on retirement and social security claiming. *Journal of Applied Econometrics*, 19(6), 761–775.
- Imbens, G. W., Rubin, D. B., & Sacerdote, B. I. (2001). Estimating the effect of unearned income on labor earnings, savings, and consumption: Evidence from a survey of lottery players. *American Economic Review*, 91(4), 778–794.
- Jarnebrant, P., & Myrseth, K. O. R. (2013). Mortality beliefs distorted: Magnifying the risk of dying young.
- Kalda, A. (2020). Peer financial distress and individual leverage. The Review of Financial Studies, 33(7), 3348–3390.
- Kaustia, M., & Knüpfer, S. (2008). Do investors overweight personal experience? Evidence from IPO subscriptions. The Journal of Finance, 63(6), 2679–2702.
- Knüpfer, S., Rantapuska, E., & Sarvimäki, M. (2017). Formative experiences and portfolio choice: Evidence from the finnish great depression. The Journal of Finance, 72(1), 133–166.
- Kuchler, T., & Zafar, B. (2019). Personal experiences and expectations about aggregate outcomes. The Journal of Finance, 74(5), 2491–2542.
- Kárpáti, D. (2022). Household finance and life-cycle economic decisions under the shadow of cancer. Working paper.
- LaBar, K. S., & Cabeza, R. (2006). Cognitive neuroscience of emotional memory. Nature Reviews Neuroscience, 7(1), 54–64.
- Li, Z., & Dalaker, J. (2021). Poverty among americans aged 65 and older. Washington, DC: Congressional Research Service.
- Liu, W.-M., Forbat, L., & Anderson, K. (2019). Death of a close friend: Short and long-term impacts on physical, psychological and social well-being. *PloS one*, 14(4), e0214838.
- Malmendier, U. (2021). Experience effects in finance: Foundations, applications, and future directions. Review of Finance, 25(5), 1339–1363.
- Malmendier, U., & Nagel, S. (2011). Depression babies: do macroeconomic experiences affect risk taking? The Quarterly Journal of Economics, 126(1), 373–416.
- Malmendier, U., & Nagel, S. (2016). Learning from inflation experiences. The Quarterly Journal of Economics, 131(1), 53–87.
- Malmendier, U., Pouzo, D., & Vanasco, V. (2020). Investor experiences and financial market dynamics. Journal of Financial Economics, 136(3), 597–622.
- Post, T., & Hanewald, K. (2013). Longevity risk, subjective survival expectations, and individual saving behavior. Journal of Economic Behavior & Organization, 86, 200–220.

- Puri, M., & Robinson, D. T. (2007). Optimism and economic choice. Journal of Financial Economics, 86(1), 71–99.
- Smith, V. K., Taylor, D. H., & Sloan, F. A. (2001). Longevity expectations and death: Can people predict their own demise? *American Economic Review*, 91(4), 1126–1134.
- Spaenjers, C., & Spira, S. M. (2015). Subjective life horizon and portfolio choice. Journal of Economic Behavior & Organization, 116, 94–106.
- Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199.
- Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. Journal of Financial Economics, 101(2), 449–472.
- Wisman, A., & Goldenberg, J. L. (2005). From the grave to the cradle: Evidence that mortality salience engenders a desire for offspring. *Journal of Personality and Social Psychology*, 89(1), 46.

# Tables

**Table 1:** This table presents the summary statistics for the HILDA panel for the years 2001 to 2019. The upper panel shows the variables on individual level whereas the lower panel shows the variables on a household level. Columns 1 to 4 display the mean, median, standard deviation and number of observations for the whole sample.

	Mean	Median	SD	Observations
Individual level				
Female	0.51	1	0.50	387,010
Age	36.99	36	22.39	380,262
Death friend	0.11	0	0.31	242,743
Live to 75?	3.30	3	0.75	$46,\!549$
Saving habit	3.33	3	1.21	143,393
Saving horizon	2.87	3	1.53	143,000
Risk aversion	5.36	5	2.47	$253{,}549$
Coldness	2.18	2	1.33	19,8235
Household level				
Income (in AUD)	$75,\!426.30$	$59,\!535$	$71,\!560.32$	$158,\!276$
Saving rate	0.54	0.62	0.26	114,439
Fun expenditure	0.09	0.07	0.07	120,708
Necessities expenditure	0.25	0.21	0.14	$121,\!259$
Health expenditure	0.05	0.04	0.04	117,766

**Table 2:** This table shows detailed summary statistics related to the main independent variable of interest. Panel A shows the relative and absolute frequency of the death of a close friend indicator for various age groups. Panel B displays the correlation coefficients between the death of a close friend indicator variable and several demographic variables.

I and III IIgo Di						
Age	18-30	30-40	40-50	50-60	>60	Overall
Relative	0.066	0.063	0.092	0.125	0.208	0.112
Absolute	$3,\!552$	2,582	$3,\!942$	$4,\!807$	$11,\!298$	$27,\!078$

<b>Panel A:</b> Age Distribution
----------------------------------

	Death		Saving			Edu-			Live
	friend	Income	Rate	Female	Age	cation	Health	$\operatorname{Smoker}$	to $75$
Death friend	1.000								
Income	-0.065	1.000							
Saving Rate	-0.071	0.483	1.000						
Female	0.006	-0.022	-0.025	1.000					
Age	0.172	-0.106	-0.106	0.032	1.000				
Education	-0.063	0.211	0.145	-0.044	0.014	1.000			
Health	-0.096	0.164	0.137	-0.013	-0.295	0.131	1.000		
Smoker	0.020	-0.090	-0.073	-0.062	-0.132	-0.123	-0.125	1.000	
Live to 75	-0.071	0.157	0.128	0.092	-0.206	0.143	0.401	-0.148	1.000

#### Panel B: Correlations

Table 3: This table shows the results from regressing various saving variables on the death of a close friend dummy. In column 1, I regress the saving rate on the death of a close friend dummy. In Columns 2 and 3, I regress the saving habit variable on the lagged friend's death dummy. In columns 4 and 5, I regress the saving horizon variable on the friend's death dummy variable. Column 1 includes household and age fixed effects whereas columns 2 to 5 include person and age fixed effects. Standard errors are clustered by either individual or household level, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Saving Rate	Saving Habit	Saving Habit	Saving Horizon	Saving Horizon
Death friend(t)	-0.011*** (-3.74)			-0.019 (-1.59)	-0.019 (-1.55)
Death friend(t-1)		-0.023** (-2.16)	$-0.020^{*}$ (-1.95)		
Log Income			$\begin{array}{c} 0.108^{***} \\ (16.13) \end{array}$		$0.065^{***}$ (10.06)
Person FE	NO	YES	YES	YES	YES
Household FE	YES	NO	NO	NO	NO
Age FE	YES	YES	YES	YES	YES
Observations	92,965	99,823	99,823	123,540	123,540
Adjusted $\mathbb{R}^2$	0.454	0.454	0.457	0.455	0.456

 $t\ {\rm statistics}$  in parentheses

**Table 4:** This table shows the results of regressing saving rate and consumption components on a dummy variable that is equal to one if the death of a close friend occurred in any previous period. Column 1 shows the effect on the overall saving rate. Columns 2 to 4 group the consumption components into the categories leisure, necessities, and health and insurance. Panel A runs the regressions for the full sample, whereas panel B and C run the regressions separately for the younger than 45 and older than 45 year old. I estimate OLS regressions with household and age fixed effects. Standard errors are clustered by household, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

#### Panel A: Full sample

	Saving Rate	Expenditure on Leisure	Expenditure on Necessities	Expenditure on Health
Death friend $(t+1,T)$	-0.017***	0.006***	$0.008^{***}$	0.002***
	(-4.63)	(6.39)	(3.77)	(3.02)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	94,115	99,199	$99,\!635$	96,974
Adjusted $R^2$	0.466	0.500	0.476	0.549

#### Panel B: Younger than 45

	Saving Rate	Expenditure on Leisure	Expenditure on Necessities	Expenditure on Health
Death friend $(t+1,T)$	-0.025***	0.011***	0.008**	0.001
	(-3.71)	(6.66)	(2.03)	(1.39)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	36,777	39,046	39,098	$37,\!867$
Adjusted $R^2$	0.454	0.519	0.460	0.417

#### Panel C: Older than 45

	Saving	Expenditure	Expenditure	Expenditure
	Rate	on Leisure	on Necessities	on Health
Death friend( $t+1,T$ )	-0.013***	$0.003^{***}$	$0.008^{**}$	$0.002^{**}$
	(-2.78)	(2.89)	(2.82)	(2.28)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	56,859	59,694	60,080	$58,\!650$
Adjusted $\mathbb{R}^2$	0.471	0.492	0.490	0.542

Table 5: This table shows the results of regressing (1) the likelihood to live to 75 on the death of a close friend dummy and (2) the saving rate on the likelihood to live to 75. In columns 2 and 4, the independent variable is lagged by one year. I estimate OLS regressions with individual and age fixed effects. Standard errors are clustered by individual level, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Likelihood live to 75	Likelihood live to 75	Saving Rate	Saving Rate
Death friend(t)	-0.027** (-1.99)			
Death friend(t-1)		-0.011 (-0.82)		
Likelihood live to 75(t)			$0.005^{**}$ (2.00)	
Likelihood live to 75(t-1)				$0.005^{*}$ (1.83)
Person FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	$34,\!554$	$32,\!608$	$36,\!246$	34,117
Adjusted $R^2$	0.513	0.519	0.367	0.372

Table 6: This table shows the results of regressing the saving rate on the death of a close friend dummy for various subsamples split by source of retirement income. In columns 1 and 2, the sample is split according to whether households report that they rely on income from saving and investments for retirement. In columns 3 and 4, households are grouped by reporting that their main source of income for retirement are saving and investments. Finally, in columns 5 and 6 households are split by whether a state pension constitutes a source of income for retirement. I estimate OLS regressions with household and age fixed effects. Standard errors are clustered by household, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Retirement		Main Re	etirement	Retirement	
	Income - Saving		Income	- Saving	Income - Pension	
	No	Yes	No	Yes	No	Yes
Death friend(t)	-0.004	-0.016**	-0.007	-0.039**	-0.012	-0.008
	(-0.76)	(-2.05)	(-1.45)	(-2.09)	(-1.60)	(-1.17)
Household FE	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES
Observations Adjusted $R^2$	$20,980 \\ 0.440$	$13,406 \\ 0.476$	$31,470 \\ 0.441$	$2,960 \\ 0.514$	$19,475 \\ 0.441$	$14,902 \\ 0.443$

Table 7: This table shows the results of regressing the saving rate on the death of a close friend indicator variable splitting the households along their parenthood status. Columns 1 and 2 display the results for parents and childless individuals, respectively. Columns 3 and 4 present the results for parents where the child does not live in the household and parents living with a child. I estimate OLS regressions with household and age fixed effects. Standard errors are clustered on household level, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Savin	g Rate	Saving	Rate
	Parent	Childless	Child not in HH	Child in HH
Death friend(t)	-0.007**	-0.023***	-0.012***	0.001
	(-2.23)	(-3.14)	(-2.73)	(0.14)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	68,668	$21,\!869$	33,467	$34{,}538$
Adjusted $\mathbb{R}^2$	0.446	0.502	0.452	0.434

**Table 8:** This table shows the results from regressing various saving variables on the death of a close friend dummy. In columns 1, 3, and 5 only individuals and households aged 45 and younger are included. In columns 2, 4, and 6 only individuals and households aged 45 and older are included. I estimate OLS regressions with household and age fixed effects. Standard errors are clustered by either individual or household level, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Saving Rate		Saving	Saving Habit		Saving Horizon	
	<45	>45	<45	>45	<45	>45	
Death friend(t)	$-0.014^{**}$	-0.009**			-0.036*	-0.009	
	(-2.19)	(-2.46)			(-1.70)	(-0.62)	
Death friend $(t-1)$			-0.050**	-0.014			
			(-2.37)	(-1.17)			
Person FE	NO	NO	YES	YES	YES	YES	
Household FE	YES	YES	NO	NO	NO	NO	
Age FE	YES	YES	YES	YES	YES	YES	
Observations	36,166	54,035	46,483	52,045	62,200	60,020	
Adjusted $R^2$	0.454	0.447	0.430	0.488	0.407	0.497	

**Table 9:** This table shows the results of regressing the saving rate on a set of dummies indicating the time relative to the event of a close friend dying. Column 1 displays a regression including period -6 to +6, column 2 includes -5 to +5, and column 3 includes -4 to +4. All regressions include year times age fixed effects. Standard errors are clustered at the household level, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Saving Rate	Saving Rate	Saving Rate
Friend Death(-6)	-0.003		
	(-0.33)		
Friend Death(-5)	-0.012	-0.011	
	(-1.26)	(-1.20)	
Friend Death(-4)	-0.009	-0.008	-0.005
	(-1.00)	(-0.90)	(-0.65)
Friend Death(-3)	-0.012	-0.011	-0.008
	(-1.34)	(-1.27)	(-1.03)
Friend Death(-2)	-0.015*	-0.014*	-0.012
	(-1.86)	(-1.81)	(-1.59)
Friend Death(-1)	-0.021**	-0.019**	$-0.017^{**}$
	(-2.55)	(-2.55)	(-2.36)
Friend Death	-0.057***	-0.056***	-0.054***
	(-7.68)	(-8.02)	(-8.15)
Friend $Death(+1)$	-0.033***	-0.032***	-0.030***
	(-4.59)	(-4.72)	(-4.68)
Friend $Death(+2)$	-0.033***	-0.031***	-0.029***
	(-4.36)	(-4.46)	(-4.39)
Friend $Death(+3)$	-0.025***	-0.024***	-0.022***
	(-3.39)	(-3.44)	(-3.32)
Friend $Death(+4)$	-0.024***	-0.022***	-0.020***
	(-3.22)	(-3.27)	(-3.14)
Friend $Death(+5)$	-0.012	-0.010	
	(-1.61)	(-1.54)	
Friend $Death(+6)$	-0.007		
	(-0.93)		
Year x Age FE	YES	YES	YES
Observations	27,620	27,620	27,620
Adjusted $R^2$	0.015	0.008	0.019

Table 10: This table shows in columns 1 and 2 the results of regressing the saving rate on the death of a close friend dummy. Columns 3 and 4 display the results of regressing a dummy variable equal to one if the death of a close friend occurred in any previous period and zero otherwise. Columns 1 and 3 conduct these analyses for the high risk aversion group and columns 2 and 4 for the low risk aversion households. I run OLS regressions with household and age fixed effects. Standard errors are clustered by either individual or household level, and \*, \*\*, and \*\*\*denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively

	Saving	g Rate	Savin	g Rate
	High $\rho$	Low $\rho$	High $\rho$	Low $\rho$
Death friend( $t$ )	-0.014***	-0.025***		
	(-2.99)	(-3.25)		
Death friend(t+1,T)			-0.012* (-1.93)	-0.022*** (-2.64)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	31,443	18,554	31,015	17,921
Adjusted $R^2$	0.458	0.442	0.464	0.451

Table 11: This table shows in columns 1 and 2 the results of regressing the saving rate on the death of a close friend dummy. Columns 3 and 4 display the results of regressing a dummy variable equal to one if the death of a close friend occurred in any previous period and zero otherwise. Columns 1 and 3 conduct these analyses for the group identifying themselves as warm and columns 2 and 4 for the households identifying themselves as cold. I run OLS regressions with household and age fixed effects. Standard errors are clustered by household level, and \*, \*\*, and \*\*\*denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively

	Saving	Rate	Saving Rate	
	Not Cold	Cold	Not Cold	Cold
Death friend $(t)$	-0.015***	0.003		
	(-3.35)	(0.28)		
Death friend( $t+1,T$ )			-0.020*** (-3.22)	-0.003 (-0.18)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	$34,\!855$	7,719	39,399	8,947
Adjusted $R^2$	0.470	0.502	0.476	0.497

Table 12: This table shows the results of regressing various life choices on the death of a close friend dummy. Column 1 and 2 display the findings for the birth of a child dummy, columns 3 and 4 for the change in occupation dummy, and columns 5 and 6 for the reported average hours worked. I estimate OLS regressions with household and age fixed effects. Standard errors are clustered by either individual or household level, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Birth of child	Birth of child	Change in occupation	Change in occupation	Hours worked	Hours worked
Death friend(t)			-0.003		0.059	
			(-0.73)		(0.58)	
Death friend(t-1)	-0.002**			-0.001		0.059
× ,	(-2.14)			(-0.36)		(0.55)
Death friend(t-2)		$0.001 \\ (0.71)$				
Person FE	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES
Observations	196,760	175,118	$139{,}533$	130,499	150,163	133,061
Adjusted $R^2$	0.110	0.114	0.146	0.148	0.630	0.632

Table 13: This table shows the results from regressing the saving rate on the death of a close friend dummy while controlling for household health. Columns 1 and 2 regress the saving rate on the death of a close friend dummy variable. In columns 3 and 4, the main dependant variable is a indicator variable equal to one in all periods following the death of a close friend. Columns 5 and 6 display the results of column 1 and 2 while restricting the sample to households that do not experience a negative change to their health. All regressions include household and age fixed effects. Standard errors are clustered by household, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Saving Rate	Saving Rate	Saving Rate	Saving Rate	$\begin{array}{l} \Delta \text{ General} \\ \text{Health} >=0 \end{array}$	$\Delta \text{ Mental} \\ \text{Health} >=0$
Death friend(t)	-0.011***	-0.010***			-0.011**	-0.011***
	(-3.60)	(-3.47)			(-2.54)	(-2.87)
Death friend $(t+1,T)$			-0.036***	-0.036***		
			(-9.47)	(-9.42)		
General Health	0.029***		0.029***			
	(3.65)		(3.68)			
Mental Health		0.047***		0.048***		
		(5.84)		(5.90)		
Household FE	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES
Observations	92,205	$92,\!662$	92,931	$93,\!449$	$55,\!594$	56,823
Adjusted $\mathbb{R}^2$	0.454	0.454	0.456	0.456	0.443	0.447

Table 14: This table shows the results of regressing the saving rate on the death of a close friend indicator for various demographic sample splits. In the upper part, column 1 and 2 display the findings separately for men and women, columns 3 and 4 for individuals with university degree and no university degree, and columns 5 and 6 for low and high financial literacy households. In the lower panel, columns 1 and 2 show the findings separately for religious and non-religious, columns 3 and 4 for urban and rural households, and columns 5 and 6 depending on how long ago the death of a close friend occurred. All regressions include household and age fixed effects. Standard errors are clustered by household, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Saving	Saving Rate		Saving Rate		Saving Rate	
	Male	Female	Not Univer.	University	Low Liter.	High Liter.	
Death friend(t)	$-0.012^{***}$ (-2.58)	$-0.011^{***}$ (-2.67)	-0.009** (-2.52)	$-0.014^{***}$ (-2.74)	-0.011** (-2.37)	-0.012*** (-2.77)	
Household FE Age FE	YES YES	YES YES	YES YES	YES YES	YES YES	YES YES	
Observations Adjusted $R^2$	$45,660 \\ 0.452$	$47,303 \\ 0.454$	$47,036 \\ 0.438$	$45,928 \\ 0.445$	$33,910 \\ 0.433$	$50,823 \\ 0.454$	

	Saving Rate		Saving	Saving Rate		Saving Rate	
	Religious	Not Relig.	Urban	Rural	1-3 Months	4-12 Months	
Death friend $(t)$	-0.010***	-0.012*	-0.011***	-0.009	-0.008*	-0.010***	
	(-2.72)	(-1.90)	(-3.48)	(-1.11)	(-1.78)	(-2.77)	
Household FE	YES	YES	YES	YES	YES	YES	
Age FE	YES	YES	YES	YES	YES	YES	
Observations	53,806	31,846	77,822	14,403	92,965	105,304	
Adjusted $\mathbb{R}^2$	0.460	0.456	0.459	0.470	0.454	0.458	

 $\overline{t}$  statistics in parentheses

**Table 15:** This table shows the relative reduction in survival rate implied by the estimated reduction in saving rate. The rows represent the time periods relative to the death of a close friend. Each column displays the results for a different coefficient of risk aversion  $\rho$ . The final row shows the fitted decay parameter  $\lambda$ .

	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$	$\rho = 5$
Period 0	0.014	0.047	0.089	0.129	0.171
Period 1	0.008	0.028	0.053	0.076	0.101
Period 2	0.008	0.025	0.044	0.069	0.093
Period 3	0.007	0.021	0.037	0.055	0.072
Period 4	0.006	0.021	0.026	0.046	0.053
Period 5	0.002	0.009	0.015	0.024	0.020
Period 6	0.002	0.003	0.009	0.008	0.015
λ	1.69	1.77	2.09	1.93	2.06

**Table 16:** This table shows the results of regressing the saving rate on several demographic variables for various ways to aggregate individual data on a household level. These demographics include gender, age, age squared an indicator variable indicating that an individual has a child, educational level, self-assessed health, an indicator variable indicating that an individual is a smoker, the life expectation, and the reported life satisfaction. The aggregation modes are the first observation for a family, the mean of the observations across the family, or the most senior member of the family. All regressions include year fixed effects. Standard errors are clustered by household, and \*, \*\*, and \*\*\* denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Fi	rst	Me	ean	Senior	
	Saving Rate	Saving Rate	Saving Rate	Saving Rate	Saving Rate	Saving Rate
Female	-0.025*** (-7.70)	-0.026*** (-6.17)			-0.044*** (-11.25)	-0.042*** (-8.34)
Age	$0.006^{***}$ (10.14)	$0.005^{***}$ (6.77)	$0.006^{***}$ (10.28)	$0.006^{***}$ (7.38)	$\begin{array}{c} 0.007^{***} \\ (11.76) \end{array}$	$0.008^{***}$ (8.49)
$Age^2/100$	-0.007*** (-12.21)	$-0.007^{***}$ $(-8.65)$	$-0.007^{***}$ (-12.33)	$-0.007^{***}$ (-9.21)	-0.008*** (-12.58)	-0.008*** (-9.42)
Child	$0.059^{***}$ (18.04)	$\begin{array}{c} 0.057^{***} \\ (13.24) \end{array}$	$\begin{array}{c} 0.053^{***} \\ (16.47) \end{array}$	$\begin{array}{c} 0.051^{***} \\ (11.95) \end{array}$	$\begin{array}{c} 0.083^{***} \\ (21.57) \end{array}$	$0.076^{***}$ (14.88)
Education	$\begin{array}{c} 0.007^{***} \\ (11.47) \end{array}$	$0.007^{***}$ (8.79)	$0.009^{***}$ (12.56)	$0.008^{***}$ (9.39)	$0.007^{***}$ (8.85)	$0.007^{***}$ (7.07)
Health	$\begin{array}{c} 0.011^{***} \\ (10.25) \end{array}$	$0.006^{***}$ (3.31)	$0.010^{***}$ (13.42)	$0.007^{***}$ (6.93)	$\begin{array}{c} 0.013^{***} \\ (10.31) \end{array}$	$0.008^{***}$ (3.82)
Smoker	$-0.064^{***}$ (-16.33)	-0.057*** (-10.66)	$-0.069^{***}$ (-16.61)	$-0.060^{***}$ (-10.56)	$-0.066^{***}$ (-14.92)	-0.061*** (-9.98)
Likelihood live to 75		$0.009^{***}$ (3.03)		$0.006^{*}$ (1.94)		$0.008^{**}$ (2.33)
Life Satisfaction		$0.009^{***}$ (5.63)		$\begin{array}{c} 0.011^{***} \\ (6.99) \end{array}$		$0.009^{***}$ (5.11)
Time FE	YES	YES	YES	YES	YES	YES
Observations Adjusted $R^2$	$91839 \\ 0.078$	$19060 \\ 0.077$	$94494 \\ 0.079$	$19830 \\ 0.079$	$68323 \\ 0.089$	$\begin{array}{c} 14108 \\ 0.086 \end{array}$

**Table 17:** This table shows the parameter values for solving the life-cycle consumption model. The upper part displays the parameters that are exogenously given to describe the agent and her environment. The lower part shows the parameters determining the labor income path of an agent. These parameters are estimated from the HILDA panel data using the methodology of (Cocco et al., 2005).

Parameter		Value
Agent		
Age of first employment	$t_0$	22
Age of retirement	$\mathrm{t}_R$	65
Maximum life span	T	100
Risk aversion	$\rho$	5
Discount factor	$\beta$	0.96
Financial market		
Risk-free rate	$R_f$	1.02
Labor income		
Effect of $age/10$ on log wage	$\theta_1$	-0.022
Effect of $age^2/100$ on log wage	$\theta_2$	0.059
Effect of $age^3/1000$ on log wage	$\theta_3$	-0.008
Constant	$\theta_0$	9.664
Replacement rate in retirement		0.54
Standard deviation persistent income shock	$\sigma_{c}$	0.129
Standard deviation transitory income shock	$\sigma_{\epsilon}$	0.112

**Table 18:** This table shows alternative specifications for the main finding in table 2. Column 1 displays again the baseline specification. Column 2 implements the estimator proposed by Sun and Abraham (2021). Column 3 implements the stacked regression estimator as in cengiz2019effect. Finally, column 4 only includes households that experienced a positive change in income in the year a close friend died. All regressions include household and age fixed effects. Standard errors are clustered by household level, and \*, \*\*, and \*\*\*denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively

	Baseline	$\begin{array}{c} \text{Sun \& Abraham} \\ (2021) \end{array}$	Cengiz et al. $(2019)$	Pos. change in income
Death friend	-0.011***	-0.009**	-0.009**	-0.011***
	(-3.74)	(-2.34)	(-2.30)	(-3.21)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	92,965	105,304	4,832,060	57,594
Adjusted $R^2$	0.454	0.458	0.460	0.491

Table 19: This table shows the elicited consumption categories that I aggregate to calculate a household's total consumption. I cluster the categories into leisure related expenditure, expenditure on necessities, and health and insurance related expenditure.

Category	Expenditure on
Leisure	Alcohol, Cigarettes, Meals eaten out, Men's clothing, Women's clothing
Necessities	Groceries, Public transport and taxis, Children's clothing, Telephone rent and calls, Internet charges, Utilities, Car repairs and maintenance, Education fees, Motor vehicle fuel
Health and Insurance	Private health insurance, Other insurances, Medicines, prescriptions and pharmaceuticals, Health practitioners

**Table 20:** This table shows the absolute and relative frequency of causes of death in Australia in 2019 provided by the Australian Bureau of Statistics (ABS). I aggregate the subcategories provided by the ABS into the larger four categories: disease, accident, assault, and selfharm related causes of death. For each age group, only the ten most common causes of death are presented by the ABS. Columns 1 and 2 display the numbers for the younger than 40 year old whereas columns 3 and 4 present the numbers for the older than 40 year old.

	Absolute	Percentage	Absolute	Percentage
Disease	1,201	0.319	$152,\!587$	0.991
Accident	766	0.203	373	0.002
Assault	86	0.023		
Selfharm	1,712	0.455	$1,\!087$	0.007
Sum	3,765	1	154,047	1

# Figures

**Figure 1:** This figure shows the average wealth, consumption, saving rate, and perceived survival probabilities of the simulated life-cycle model. Each panel plots the solution for a household with objective survival probabilities (black) and a household with more pessimistic survival probabilities (red).



Figure 2: This figure shows the average wealth, consumption, saving rate, and perceived survival probabilities of an agent that receives a shock of 10 percent to her survival rate at the age of 41. The weight of the shock decays over time with a decay parameter  $\lambda$  equal to 1.5. The figure displays only the age 39 to 49. Each panel plots the solution for a household with objective survival probabilities (black) and the shocked household (red).



**Figure 3:** This figure shows the average household saving rate by age. For the left figure, the age of the first member of the household in the sample is chosen. For the right figure, the age of the most senior member of the household is chosen.



**Figure 4:** This figure shows a breakdown of the relative expenditure on the three consumption subcategories: leisure, necessities, and health/insurance. The left part displays the percentage for the younger than 45 year old whereas the right part the percentage for the older than 45 year old.



Figure 5: This figure shows the distribution of answers to the question "How likely that you will live to 75 or at least 10 more years?" for age bins of 5 years.



Figure 6: This figure shows the coefficients of regressing the saving rate on the death of a friend indicator and age and person fixed effects for 4 age groups separately. The bars indicate 95% confidence intervals. The left graph shows the same period impact whereas the right graph demonstrates the impact on the subsequent periods.



Figure 7: This figure shows the dynamic effect of the death of a close friend around the event window. The reference group is the saving rate outside of the event window. The bars indicate 95% confidence intervals adjusted for standard error clustering on household level.



# Appendix A - Variable Descriptions

Variable	Description
Female	Indicator variable equal to 1 if participant is female, 0 otherwise.
Age	Age of participant.
Income	Yearly disposable income from all sources. Households with windfall income are excluded.
Saving rate	One minus the sum of self-reported non-durable consumption divided by yearly disposable income from all sources.
Saving habit	<ul> <li>Which of the following statements comes closest to describing your (and your family's) saving habits?</li> <li>1 Don't save: usually spend more than income</li> <li>2 Don't save: usually spend about as much as income</li> <li>3 Save whatever is left over - no regular plan</li> <li>4 Spend regular income, save other income</li> <li>5 Save regularly by putting money aside each month</li> </ul>
Saving horizon	<ul> <li>In planning your saving and spending, which of the following time periods is most important to you ?</li> <li>1 The next week</li> <li>2 The next few months</li> <li>3 The next year</li> <li>4 The next 2 to 4 years</li> <li>5 The next 5 to 10 years</li> <li>6 More than 10 years ahead</li> </ul>
Fun expenditure	Sum of non-durable expenditure on leisure related categories (c.f. table 13) divided by income.
Necessities expenditure	Sum of non-durable expenditure on necessity related categories (c.f. table 13) divided by income.
Health expenditure	Sum of non-durable expenditure on health and insurance related categories (c.f. table 13) divided by income.

Continued on next page

Friend death(t)	Indicator variable equal to one if the individual reports the death of a close friend, and zero otherwise				
Friend $death(t+1,T)$	Indicator variable equal to one for each period following the death of a close friend, not including period $t = 0$ , and zero otherwise.				
Likelihood to live to 75	How likely that you will live to 75 or at least 10 more years? 1 Very likely 2 Likely 3 Unlikely 4 Very unlikely				
Risk aversion	Are you generally a person who is willing to take risks or are you unwilling to take risks? 0 Very willing to take risks  10 Unwilling to take risk				
Coldness	How well do the following words describe you? - Cold 1 Does not describe me at all  7 Describes me very well				

## Appendix B - Model and Estimation Details

#### B1 - Canonical Life-cycle Model Setup

An agent maximizes her lifetime utility. Let t be the agent's adult age and T the maximum number of periods the agent lives. Then the agent faces the following maximization problem:

$$\max \mathbb{E}\left[\sum_{t=1}^{T} \beta^{t-1} (\prod_{j=0}^{t-2} s_j) u(c_t)\right]$$

where  $c_{it}$  is the consumption of agent *i* at age *t*,  $\beta$  is the discount factor, and most importantly  $s_j$  is the agent's probability to survive from period j - 1 to *j*. I do not consider bequest motives and assume *u* to represent a power utility function. Each period the agent decides how much of his income to consume and the remainder is saved at a fixed rate of *R*.

Labor Income Process. During an agent's working age, she receives an exogenously given stochastic labor income Y:

$$log(Y_{it}) = f_t + \zeta_{it} + \epsilon_{it}$$

where  $f_t$  is a function representing the deterministic component of labor income at age t and  $\epsilon_{it}$ is an idiosyncratic shock to labor income which is distributed  $N(0, \sigma_{\epsilon}^2)$ .  $\zeta_{it}$  constitutes a persistent shock to labor income:

$$\zeta_{it} = \zeta_{i,t-1} + u_{it}$$

where  $u_{it}$  is  $N(0, \sigma_u)$  distributed and uncorrelated with  $\epsilon_{it}$  and all shocks are uncorrelated across households. After the agent reaches the age of 65, she enters retirement and her labor income becomes deterministic. It is given by the last working period's permanent income multiplied by a replacement factor.

**Optimization Problem.** All real variables are normalized by the permanent labor income  $P_t$  to reduce the dimensionality of the state space to 1. I denote all normalized variables by lower case letter. Each period, the agent has a certain amount of cash-on-hand which is the sum of her savings and savings returns and her labor income:

$$m_{it} = y_{it} + w_{it}$$

where  $w_{it}$  is given by:

$$w_{it} = R(w_{i,t-1} + y_{i,t-1} - c_{i,t-1})$$

The agent maximizes (B1) under all of these conditions. The Bellman equation is given by:

$$\nu_{it}(m_{it}) = \max_{c_{it}} u(c_{it}) + \beta s_{i,t+1} \mathbb{E}[(p_{i,t+1}/p_{it})^{1-\rho} \nu_{i,t+1}(m_{i,t+1})]$$

There is no analytical solution to this problem. Hence, the policy functions are solved numerically.

#### B2 - Solving the Model

The model is solved by backward induction. The solution for the last period is trivial as the agent consumes all of her remaining wealth. Hence, in the second to last period one can plug in the indirect utility function for next period's value function. Based on this, it is possible to derive a consumption function that gives the optimal level of consumption given a certain level of wealth (cash-on-hand). Furthermore, one can derive the value function for the second to last period. To obtain the solution for all periods, one iterates backwards from the last to the first period.

Unfortunately, there is no analytical solution to the maximization problem. In practice, to reduce computational load I construct a discrete grid of possible cash-on-hand levels and find the optimal level of consumption for each of these grid points. Finally, the grid points are interpolated to construct the consumption function. For the graphs, I simulate the outcomes for 5000 agents and average over outcomes<sup>5</sup>.

#### B3 - Fitting the Empirical Results to the Model

I estimate the implied reduction in survival rate and the associated decay in effect based on the reduction in saving rate observed in the data following the death of a close friend. I do not directly observe the impact of the shock on the survival rate. However, the rareness of the event of a close friend dying greatly reduce the complexity of the problem: (1) The initial shock represents 100% of the set of experiences. Hence, I can normalize all further effects by the initial shock. (2) The initial shock remains the only component of the set of relevant experiences as the agent is not exposed to any new experiences. Thus, I can directly compare the subsequent changes in survival rate to the initial reduction in survival rate to elicit the weight of the first experience in these later periods. Table 15 illustrates this in more detail. Panel A shows how much weight past experiences receive at various ages given a decay parameter  $\lambda$  of 2. For example, at age 0 the agent only has made the experience of that period which receives a weight of 1. Next, at age 1 the experience in period 0 receives a weight of 0.2 and the experience in the same period 0. Hence, the weight of all other periods is multiplied by zero at all subsequent ages. Panel B shows the corresponding reduction of

<sup>&</sup>lt;sup>5</sup>For setting up and solving the model I utilize the *Heterogeneous Agents Resources and toolKit (HARK)* by Carroll et al. (2018)

the initial effect for all ages. For example, at age 1 only 20 percent of the initial effect should be observable. Then, in the next year only 7.2 percent of the initial shock are observable and so forth.

I take this intuition to the empirical results. In a first step, I estimate the corresponding drop in perceived survival rate associated with the reduction in saving rate estimated from the data. For that purpose, I fit the survival rate separately for each period after the shock. I simulate the saving rate for a list of relative reductions in survival rate from 0.3 to 0 in steps of 0.001. Then, I select the relative reduction in survival rate that corresponds to the survival rate estimated in that period in table 6. This gives rise to a list of relative reductions in survival rate for each of the seven periods following the mortality beliefs shock. I repeat this procedure for a list of coefficients of relative risk aversion ranging from 1 to 5. In a second step, I estimate the  $\lambda$  that fits the implied reductions in survival rate best. First, I calculate the weights of the period 0 experience for all 6 periods following the initial shock for a grid of  $\lambda$  ranging from 0 to 5 in steps of 0.01. Then, I find the squared distance between the in the previous step calculated weights and the implied reductions in survival rate which gives me the best fitting  $\lambda$ . Finally, I make sure this represents a global minimum.

**Table 21:** This table shows for various ages the weights of personal experiences for a decay parameter  $\lambda$  equal to 2. Panel A exhibits the weights of each period for the ages 0 to 5 of an agent. The rows represent an agent's age whereas the columns display the weight of the past period. Panel B shows the weights at each age of an agent if she only had one experience at the age of 0.

Panel A:									
	Period 0	Period 1	Period 2	Period 3	Period 4	Period 5			
Age 0	1	-	-	-	-	-			
Age 1	0.200	0.800	-	-	-	-			
Age $2$	0.072	0.286	0.643	-	-	-			
Age 3	0.033	0.133	0.300	0.533	-	-			
Age $4$	0.018	0.073	0.164	0.291	0.455	-			
Age 5	0.011	0.044	0.099	0.176	0.275	0.396			
Panel B:									
	Period 0	Period 1	Period 2	Period 3	Period 4	Period 5			
Age 0	1	-	-	-	-	-			
Age $1$	-	0.200	-	-	-	-			
Age $2$	-	-	0.072	-	-	-			
Age 3	-	-	-	0.033	-	-			
Age 4	-	-	-	-	0.018	-			
Age 5	-	-	-	-	-	0.011			