Household Finance and Subjective Beliefs

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Für Jisu.

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Frederik Horn Mannheim, October 2023

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Chapter I

Introduction

Beliefs are a crucial component of economic models. Every economic decision is characterized by individuals forming beliefs about the future which guide their decisions (Bachmann et al., 2022). In particular, households need to form beliefs about a wide range of domains like inflation, housing, education, mortality, and labor income risk. These beliefs affect then every facet of household's financial decision making like insurance choices, saving behavior, borrowing behavior, portfolio allocation, and housing choices. Yet, empirically financial decisions of households often deviate from the rational benchmark suggesting that households hold beliefs that deviate systematically from the objective ex-post probabilities. Hence, researchers are interested in the actual beliefs households hold which are called subjective beliefs.

More specifically, researchers are exploring the following questions surrounding subjective economic beliefs. How are beliefs formed? Are beliefs unbiased? Do beliefs affect household's decision making? How do beliefs impact household's financial outcomes? All three chapters of my dissertation explore questions related to subjective household beliefs and their impact on households' decision making. I use beliefs elicited in surveys and explore their impact on consumption and saving decisions, portfolio choices, and voting behavior of households.

My dissertation consists of three chapters. Each of the chapters represents a paper written during my PhD and I am the sole author of each of the papers. In the second chapter of my dissertation, I address the research question whether individuals consider subjective mortality beliefs in their saving and consumption decisions. From a theoretical point of view, the timing of an individual's death is one of the most important determinants of her intertemporal decision-making. Intuitively, an individual has to save a lot less during her working years if her life ends shortly after retirement compared to if she is blessed with a late death.

I utilize the death of a close friend as an exogenous shock to mortality beliefs and demonstrate that households significantly reduce their saving rate in response to the shock. This finding establishes empirically that indeed households consider subjective mortality beliefs in their saving decisions. Furthermore, I argue that the household's reaction to the shock can be best understood in the framework of the seminal life-cycle model of consumption and saving augmented by the experience-based learning model of Malmendier (2021). Based on this model, I quantify the impact of a personal experience on the belief formation process and show that individuals appear to significantly adjust their longevity expectations downwards. In this chapter, I contribute to a better understanding of how beliefs are formed and whether beliefs affect the financial decision-making of households.

In the third chapter, I start from the novel empirical fact that households severely overestimate the probability of losing their job in the future. Hence, their unemployment beliefs and thereby their subjective labor income risk is severely distorted. From a theoretical point of view, an increase in imperfectly insurable labor income disaster risk crowds out other sources of risk a household is willing to take on. Hence, households should be less willing to invest into risky assets like stocks.

Hence, I argue in this chapter that the low stock market investment rates of households around the world can be understood by considering subjective beliefs about future labor income. First, I demonstrate empirically that changes in unemployment beliefs significantly reduce household's investment into the stock market. Second, I structurally estimate a life-cycle model of portfolio choice that incorporates the empirical distortion in unemployment expectations. The model matches the evolution of wealth, equity share and participation rates with more plausible risk aversion estimates than the model with objective beliefs. Therefore, I address in this chapter the questions whether beliefs are unbiased and how distorted beliefs affect financial decision making.

However, beliefs about a household's financial situation can also affect non-financial decisions. In the fourth chapter of my dissertation, I explore how perceived labor income risk could induce populist voting behavior. I argue that that voting for either right-wing and left-wing populist parties can be perceived as insurance against future labor income shocks. Right-wing populist parties promise to limit immigration and protect voters against the consequences of globalization. Thus, they reduce voters' perceived labor income risk associated with foreign labor and product market competition. Left-wing populist parties advocate for an expansion of the social safety net which reduces labor income risk associated with unemployment.

I find that perceived labor income risk is strongly correlated with populist voting and that near term beliefs about labor income risk determine whether an individual decides to vote for a right-wing or left-wing populist party. Furthermore, I test the channels proposed by the economic literature but find little support for these explanations. In this chapter, I contribute to a better understanding of how economic beliefs can shape voting behavior.

Chapter II

Mortality Beliefs and Saving Decisions: The Role of Personal Experiences

Abstract

This paper is the first to establish a causal relationship between households' subjective mortality beliefs and subsequent saving and consumption decisions. Motivated by prior literature on the effect of personal experiences on individuals' belief 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 2.2 percentage points which persist over the following 5 years. Furthermore, I quantify the impact of this personal experience on mortality beliefs using the life-cycle model of consumption augmented by the experienced-based learning model. Even though the shock has no material impact on a household's situation, I find a quantitatively large initial reduction in expected survival probability of around 4 percent.

1 Introduction

Households' beliefs are a crucial part of their economic decision-making. In particular, mortality beliefs affect a wide range of economic decisions like insurance choices, health-care planning, and most notably saving and consumption 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 saving decisions. It is difficult to demonstrate a causal link between mortality beliefs and saving decisions due to 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 exploit the death of a close friend as a shock to an individual's mortality beliefs. This plausible exogenous shock allows me to causally demonstrate that more pessimistic mortality beliefs translate into lower saving rates.

Recent evidence suggests that personal experiences are an important component of the belief formation process (Malmendier & Nagel, 2011, 2016; D'Acunto et al., 2021). To quantify the impact of this non-material personal experience on the belief formation process, I augment the classic life-cycle model of consumption and saving by the experienced-based learning model of Malmendier (2021). Typically, it is challenging to compute the impact of personal experiences on the belief formation process as beliefs are inherently difficult to observe and personal experiences often affect both beliefs as well as the economic situation of a household. The staggered but rare nature of my shock allows me to isolate the impact of one personal experience on household's economic outcomes from which I can deduce the impact on the belief formation process.

Hence, in my paper I address two questions. Do individuals consider mortality beliefs in their saving decisions? How large is the impact of a personal experience on the belief formation process? To answer these questions, I use a long-running representative panel covering the Australian population to exploit the death of a close friend as an exogenous shock to the mortality beliefs of an individual. The survey covers around 17,000 Australians each year since 2001. 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.

First, I establish a causal relationship between mortality beliefs and saving decisions. Utilizing the death of a close friend as an exogenous shock to mortality beliefs, I find that the shock reduces the saving rate by a 2.2 percentage points. Considering the non-material nature of the shock, the effect size is considerable. Furthermore, this reduction in saving rate persists for the 5 following years. This suggests that it is not driven by a short-term emotional reaction but rather induced by a more long-term change in mortality beliefs. I utilize two self-reported proxies for a household's saving behavior to establish the robustness of the main findings. I find that survey participants report less regular saving habits and a significantly shorter saving horizon following the shock.

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 with a weak bequest motive. These analyses demonstrates that the exogenous shock works through the intended channel of more pessimistic mortality beliefs. The data allows me to break the effect on the saving rate down into consumption subcategories. This analysis reveals that the reduction in saving rate is not caused by increased concerns about one's own health as health expenditure is barely affected. On the contrary, consumption of leisure related items like alcohol or meals eaten out increases the most. Moreover, the results are not driven by bequests of the deceased friend, drastic life changes, or reductions in income.

Second, I use the life-cycle model of consumption and saving augmented by the experienced-based learning model of Malmendier (2021) to derive two unique predictions which I test empirically. On the one hand, the agent's age crucially determines how strongly she should be affected by the shock. 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. Indeed, I find that younger individuals reduce their saving rate three times more than older individuals (3.5 versus 1.2 percentage points). On the other hand, the canonical life-cycle model predicts that the agent's reaction to the shock crucially depends on her risk-aversion. Intuitively, more risk-averse agents should react less to an increase in longevity risk. I find that more risk-loving households reduce their saving rate by 3.2 percentage points whereas more risk-averse households only lower their saving rate by 1.2 percentage points. These results suggest that the experience-based learning model in the context of the life-cycle model helps to understand how personal experiences are incorporated into the belief formation process.

Third, I quantify the impact of the shock on mortality beliefs in the context of the canonical life-cycle model of consumption. For that purpose, I use the augmented life-cycle model to structurally estimate both the impact of the personal experience on mortality beliefs as well as the parameters that govern how fast the shock fades out of the set of relevant experiences. I find that depending on an agent's risk aversion the death of a close friend leads to a reduction in expected probability of surviving to the next period of 1.2 percent to 13.6 percent. This reduction in expected survival probability slowly attenuates to zero over the following 6 years. The magnitude of the effect is quantitatively large considering the non-material nature of the death of a close friend. On top of that, I estimate that the parameter λ that governs how fast the experience fades out of memory ranges from 1.1 to 1.3. This is in line with estimates of Malmendier and Nagel (2011) who find estimates ranging from 1.3 to 1.9 in the vastly different domain of stock returns.

Overall, these results establish a causal link between mortality beliefs and households' saving decisions. An exogenous shock to mortality beliefs induces a significant reduction in saving behavior. I provide evidence that experience-based learning has a quantitatively large impact on the belief formation process. Moreover, my results suggest that the shape of the weighting function governing how fast experiences fade out of memory is similar across domains.

My 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) try 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.[1]

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 literature by demonstrating that personal experiences also play an important role for the belief formation process in the domain of mortality. Furthermore, I am able to quantify the impact of one personal experience on beliefs. Thus, I gauge the importance of personal experiences for financial outcomes beyond purely

[1]There is also recent concurrent work by Kárpáti (2022) who exploits genetic testing to establish a causal link between objective mortality risk and a wide range of financial outcomes in a representative Dutch dataset.

demonstrating a link.

Finally, 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 results 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.

This 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 experience-based 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 presents and discusses the main empirical results of my paper. In section 5, I structurally estimate the impact of the shock on mortality beliefs. Finally, section 6 shows robustness checks and 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 labor 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. This gives rise to the following maximization problem:

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

where c_t is a household's consumption, β a time discount factor, and $\mathbb{E}(s_j)$ the expected probability of survival to period $j+1$. Given that the agent exhibits a power utility function, one can rewrite this problem in recursive form as a Bellman equation:

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

with:

$$m_{t+1} = m_t - c_t + y_{t+1} \tag{3}$$

where m_{t+1} is the available resources next period that could be potentially used for consumption and y_{t+1} is next period's labor income. Furthermore, p_t is the permanent labor income in period t, and ρ is the coefficient of relative risk aversion of a power utility function. Taking the derivative gives rise to the following first order condition:

$$0 = u^{'}(c_t) - \beta\mathbb{E}_t(s_t)\mathbb{E}[R(p_{t+1}/p_t)^{-\rho}\nu_{t+1}(m_{t+1})] \tag{4}$$

Solving for c_t yields the following optimal consumption in t:

$$c_t^* = (\beta\mathbb{E}(s_t))^{-1/\rho}(\mathbb{E}[\cdot])^{-1/\rho} \tag{5}$$

Even though there is no analytical solution to this problem, it is straightforward to see from the optimal consumption equation that a decrease in expected survival probability leads to an increase in consumption and thereby to a reduction in the savings rate. In this paper, I argue that the death of a close friend increases the salience of death for an individual. Subsequently, she becomes more pessimistic about her mortality beliefs, resulting in a lower survival rate s_t. 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. For illustrative purposes, I solve it numerically for (1) survival rates taken from the Australian Bureau of Statistics and (2) agents that hold 5 percent more pessimistic *expected* survival probabilities relative to the objective survival probabilities.

Figure II.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).

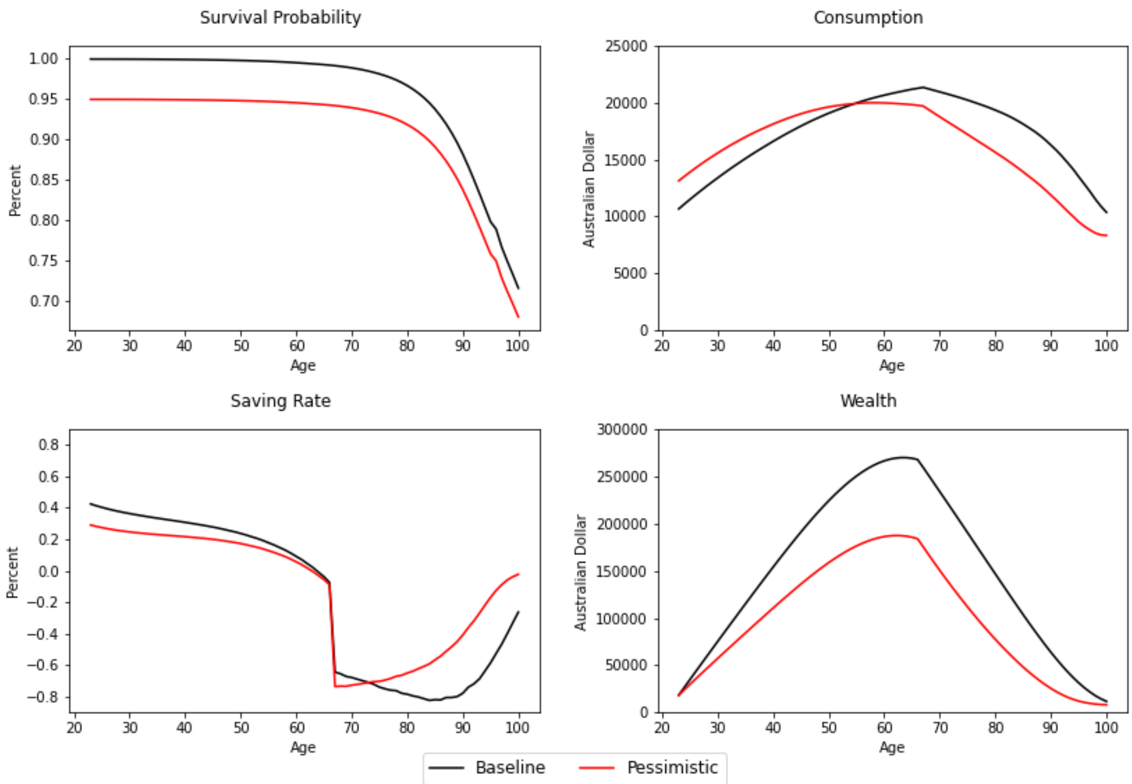


Figure II.1 shows from upper left to lower right the survival probabilities, average consumption, average saving rate, and wealth accumulation of the simulated households over the life-cycle. The black line displays the results for the simulation with the objective survival probabilities, and the red line displays the agents with pessimistic expectations about their survival probabilities. The upper right panel demonstrates that pessimistic mortality beliefs result in overconsumption in younger years. However, at around age 50 the agents with distorted beliefs are starting to underconsume as their previous saving rate does not lead to a sufficient capital stock to comfortably smooth consumption in later years. The lower right panel clearly shows that the pessimistic agents accumulate a lot less wealth over their lifespan which results in a reduced consumption in retirement.

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 (2021) 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 expected survival rate in that period. In each period, the agent weighs these past periods depending on how long ago they have occured and forms the expectation about her survival rate for the current period. I argue that expectations about the probability of surviving to the next period are given by the following equation:

$$\mathbb{E}_t(s_t) = \Gamma_t(X, a) + \sum_{k=0}^{t} w(\lambda, k, t) M_{t-k} + \epsilon_t \tag{6}$$

where Γ_t is the baseline probability of surviving to the next period for an individual at age a with a vector of personal characteristics X. These personal characteristics could include whether she is a smoker, has a chronic health condition, or is working in an unsafe occupation. $w(\lambda, k, t)$ is the weight the agent assigns to the personal experience M that occurred k years before year t and λ governs the shape of that weighting function. ϵ_t is the idiosyncratic error of an individual when forming expectations which is normally distributed with mean zero. I use the weighting function proposed by Malmendier, Pouzo, and Vanasco (2020):

$$w(k, \lambda, t) = \frac{(t+1-k)^{\lambda}}{\sum_{k\prime=0}^{t}(t+1-k')^{\lambda}} \tag{7}$$

where w is the weight an agent at t assigns to the personal experience experienced k periods ago. The parameter λ determines the weight of more recent compared to less recent experiences. Intuitively, more distant experiences receive less weight if the λ is larger. 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 is attenuated in the following periods.

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 II.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.

My main dependant variable is an individual's saving behavior. I use three measures to elicit an individual's savings decision. First, I 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[2]. These items include for example groceries, alcohol, clothing, pharmaceuticals, and many others. For a comprehensive list refer to Table II.5. Following Dynan, Skinner, and

[2]If several members of the household provided answers, the responses were averaged by HILDA.

Table II.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.

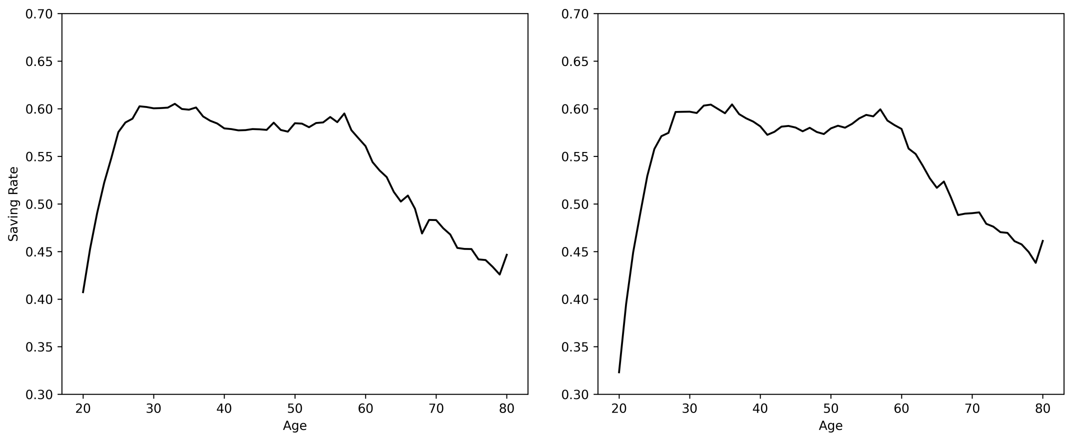
	Mean	Median	SD	Observations
Individual level				
Female	0.51	1	0.50	387,010
Age	36.99	36	22.39	380,262
Death friend	0.11	0	0.31	242,743
Live to 75?	3.30	3	0.75	46,549
Saving habit	3.33	3	1.21	143,393
Saving horizon	2.87	3	1.53	143,000
Risk aversion	5.36	5	2.47	253,549
Coldness	2.18	2	1.33	19,8235
Household 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

Zeldes (2004), I calculate the saving rate as one minus the sum all of these expenditures divided by the total after-tax 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. Figure II.2 shows the average saving rate by age. The graph displays the typical hump-shaped age profile (e.g. Guvenen, 2007; Aguiar & Hurst, 2013) which suggests that the aggregated consumption represents a sensible proxy for a household's saving rate.

Second, 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"*. Third, participants are asked about their saving horizon with possible answers ranging from *"the next week"* to *"more than 10 years ahead"*.

Figure II.2: 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.



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 very likely that they will live to 75. Only around 12 percent of individuals respond that it is unlikely or very unlikely that they are going to live to 75. Furthermore, 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.

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 subjective 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). Thus, I estimate the staggered differences-in-differences models both for the average effect and for event studies. For the average effect I use the following regression model:

$$S_{it} = \beta FD_{i,t} + \gamma_t + \delta_i + \epsilon_{it} \tag{8}$$

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 is an indicator variable equal to one for each year after the death of a close friend was reported. For couples, this indicator variable turns one as soon as both partners reported the death of a close friend. Finally, γ_t are age fixed effects and δ_i either person or household fixed effects. Hence, the β captures the average change in saving rate of treated households after the shock compared to untreated households. Furthermore, I also explore the dynamics around the shock to test for pretrends and to better understand the reaction over the following years. Hence, I estimate the following regression model:

$$S_{it} = \sum_{k=-5}^{k=5} \beta_k FD_{i,k} + \gamma_t + \delta_i + \epsilon_{it} \tag{9}$$

where $FD_{i,k}$ are time dummies relative to the death of a close friend ranging from 5 years before to 5 years after. Hence, β_k captures the change in saving rate of treated households in the years around the event compared to untreated households.

4 Empirical Results

4.1 Impact of the Shock on Saving Behavior

First, I establish that the exogenous shock to mortality beliefs indeed has an impact on the saving behavior of a household. Column 1 of table II.2 reports the results of regressing the household's saving rate on a indicator variable equal to one in all periods following the death of a close friend. All regressions include both household as well as age fixed effects[3]. Furthermore, I cluster standard errors on household level to account for auto-correlation (Bertrand et al., 2004). I find that the death of a close friend reduces the saving rate on average by 2.2 percentage points. This effect is highly significant at the 1 percent level. This result suggests that the death of a close friend induces more pessimistic mortality beliefs which translate into a lower saving rate.

Furthermore, I explore the saving rate dynamics around the shock. Columns 2 exhibits the results of regressing the saving rate on 5 pre-treatment dummies and 5 post-treatment dummies. Figure II.3 visualizes the regression results. Prior to the shock, there is no significant pretrend observable. However, as soon as the death of a close friend occurs households instantly reduce their saving rate by around 2 percentage points. Over the following 5 years, this effect attenuates to 1 percentage point. One potential concern could be that the death of a close friend induces a strong emotional reaction which results in an immediate increase in expenditure to distract oneself from the event. This could lead to a mechanical short-term increase in expenditure which is not caused by more pessimistic mortality beliefs. However, this concern becomes highly unlikely given that there is a persistent long-term reaction to the shock observable over the following 5 years.

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). These estimators only include never-treated or last-treated households in the control group and thereby create a "clean" control group. Columns 3 and 4 demonstrate that the results of the alternative estimators barely deviate from the OLS estimates. Again, the initial reduction in saving rate is around 1.9 percentage points which is highly significant at the 1 percent level.

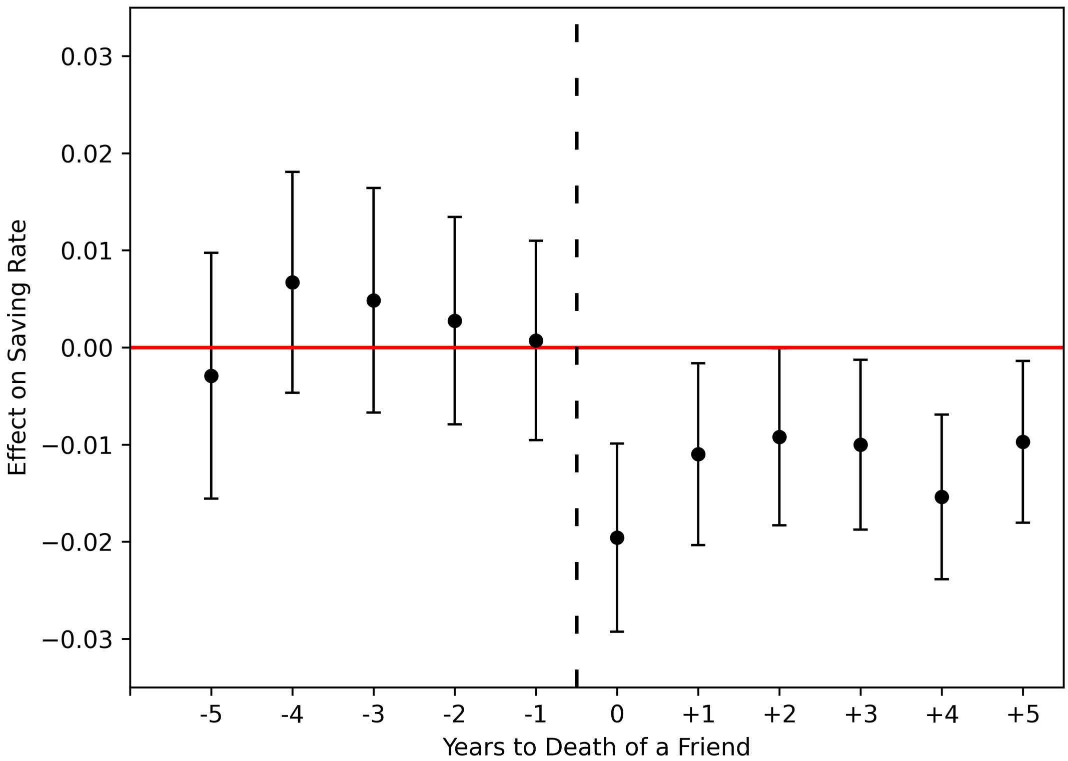
Furthermore, I exploit two additional proxies for a household's saving behavior to establish that the shock induces a reduced inclination to save. I regress the *Saving Habit* and *Saving Horizon* variables on an indicator variable equal to one if the death of a close friend was reported in that period. I conduct the analyses on the level of an individual

[3] In the online appendix, I conduct the same analysis with person and age times year fixed effects. The coefficients and statistical significance remain unchanged.

Table II.2: This table shows the results from regressing the saving rate on the death of a close friend indicator variable. In column 1, I regress the saving rate on an indicator variable equal to one if the shock occurred in any previous period. In Columns 2 to 4, I regress the saving rate on indicator variables equal to one in the 10 years surrounding the shock. In columns 1 and 2, I run OLS regressions. In column 3 and 4, I use the Sun & Abraham (2021) estimator and the Cengiz et al. (2019) estimator, respectively. 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.

	Saving Rate			
	OLS	OLS	Sun & Abraham (2021)	Cengiz et al. (2019)
Friend Death	-0.022***			
	(-5.42)			
Friend Death (-5)		-0.003	-0.001	-0.003
		(-0.45)	(-0.19)	(-0.40)
Friend Death (-4)		0.007	0.008	0.007
		(1.16)	(1.24)	(1.21)
Friend Death (-3)		0.005	0.006	0.005
		(0.82)	(0.89)	(0.91)
Friend Death (-2)		0.003	0.005	0.003
		(0.51)	(0.84)	(0.61)
Friend Death (-1)		0.001	0.003	0.001
		(0.14)	(0.60)	(0.18)
Friend Death (t=0)		-0.020***	-0.017***	-0.019***
		(-3.96)	(-3.36)	(-3.88)
Friend Death (+1)		-0.011**	-0.010**	-0.011**
		(-2.30)	(-2.01)	(-2.21)
Friend Death (+2)		-0.009**	-0.007	-0.009**
		(-1.98)	(-1.37)	(-2.00)
Friend Death (+3)		-0.010**	-0.008*	-0.010**
		(-2.25)	(-1.80)	(-2.33)
Friend Death (+4)		-0.015***	-0.014***	-0.016***
		(-3.56)	(-3.07)	(-3.64)
Friend Death (+5)		-0.010**	-0.008*	-0.010**
		(-2.29)	(-1.79)	(-2.38)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	98,946	100,218	100,218	966,539
Adjusted R^2	0.462	0.462	0.463	0.465

Figure II.3: This figure plots the point estimates of column 2 of table II.2. The bars around the point estimate indicate the 95 percent confidence intervals.



as the survey elicits these variables at this aggregation level. 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.

Columns 1 and 3 of table II.3 show that the shock both reduces the self-reported saving habit as well as the individual's saving horizon. Yet, the impact on the latter is not statistically significant at the 10 percent level. This is not surprising as older individuals are not likely to adjust their saving horizon as they approach death. Hence, in columns 2 and 4 I repeat the analysis for working age individuals. Indeed, the shock

Table II.3: This table shows the results from regressing the *Saving Habit* or *Saving Horizon* variable on the death of a close friend indicator variable. In columns 1 and 2, I regress the *Saving Habit* on an indicator variable equal to one if the shock occurred in the previous year. In Columns 3 and 4, I regress the *Saving Horizon* variable on an indicator variables equal to one in the year of the shock. Columns 2 and 4 display the results for the subsample of individuals that are 65 years or younger. All regressions include person and age fixed effects. Standard errors are clustered by person level, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Saving Habits		Saving Horizon	
	Full Sample	Younger than 65	Full Sample	Younger than 65
Friend Death(t-1)	-0.023**	-0.030**		
	(-2.16)	(-2.25)		
Friend Death(t)			-0.019	-0.031**
			(-1.59)	(-2.12)
Person FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	123,540	102,506	99,823	80,906
Adjusted R^2	0.454	0.455	0.458	0.456

t statistics in parentheses

induces a statistically significant reduction in the reported saving horizon of the younger subsample. Overall, these additional results strengthen the argument that the death of a close friend represents an exogenous negative shock to an individuals mortality beliefs which results in a lower saving rate. Especially, the finding that individuals significantly reduce their saving horizon suggests that they hold more pessimistic mortality beliefs.

In conclusion, these findings 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, at this point it is not possible to definitely conclude that the shock works through the intended channel of mortality beliefs. Hence, in the next sections I exclude possible alternative channels and directly link the shock to a reduction in mortality beliefs.

4.2 Expenditure Subcategories

One possible explanation for the reduction in saving rate could be that the shock prompts individuals to be concerned about their own health which would result in increased health care spending. However, my data allows me to test for this concern explicitly. Thus, I explore which components of consumption increase most following the shock. I cluster the various consumption subcategories elicited by the HILDA survey into three groups: leisure related expenditure, expenditure on necessities, and health and insurance related expenditure. For details refer to table II.5.

Table II.4: This table shows the results of regressing saving rate and consumption components on a dummy variable that is equal to one in each period following the death of a close friend. 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. 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.

	Saving Rate	Expenditure on Leisure	Expenditure on Necessities	Expenditure on Health
Friend Death	-0.022***	0.006***	0.012***	0.002***
	(-5.42)	(5.77)	(5.01)	(2.78)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Percentage of overall expenditure		21%	67%	12%
Observations	98,946	104,384	104,858	101,911
Adjusted R^2	0.462	0.494	0.468	0.545

t statistics in parentheses

Table II.4 reports the results of regressing the saving rate as well as the expenditure on the aforementioned categories divided by income on the friend of a death indicator variable. Columns 2 indicates that following the shock the expenditure on leisure related items increases by 0.6 percentage points which is highly significant at the 1 percent level. Similarly, columns 3 and 4 show that the shock increases expenditure on necessities and health related items by 1.2 and 0.2 percentage points, respectively. Both coefficients are highly significant at the 1 percent level. Moreover, the table reports the percentage of each of these expenditure categories of overall expenditure. Relating the regression coefficients to the unconditional expenditure percentage reveals that expenditure on leisure is affected the most by the shock as it increases by 2.8 percent relative to the baseline. Conversely, the expenditure on healthcare related items is affected the least as it increases only by

1.6 percent relative to the baseline.

Table II.5: 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.

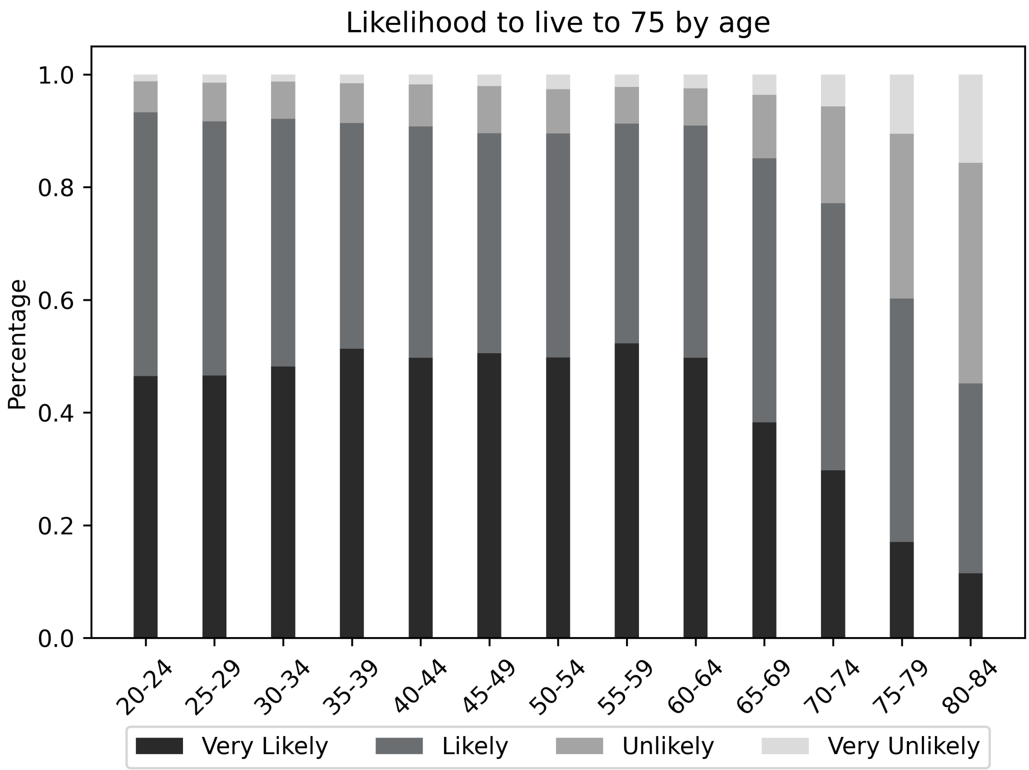
Category	**Expenditure on ...**
Leisure	Alcohol, Cigarettes, Meals eaten out, Men's clothing, Women's clothing
Necessities	Groceries, Public transport and taxis, Children's clothing, Telephone rent and calls, Internet charges, Utilities, Car repairs and maintenance, Education fees, Motor vehicle fuel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

Overall, these findings indicate that the reaction to the shock is not driven by households massively increasing their expenditure on health related items. Treated households rather increase their consumption of leisure related items like cigarettes, alcohol, and meals eaten out. These are consumption items that tend to be detrimental to one's health. Hence, it is unlikely that concerns about one's health induced by the shock are responsible for the large reduction in saving rate.

4.3 Mortality Beliefs

The necessary condition for the death of a close friend being a plausible shock is that it in fact has a negative impact on subjective 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 are strongly correlated with saving decisions (e.g. Heimer et al., 2019). Figure II.4 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 scale by participants.

Figure II.4: 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. Individuals older than 65 are asked instead "How likely that you will live ten more years?".



Columns 1 and 2 of table II.6 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.

Table II.6: 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
Friend Death(t)	-0.027**			
	(-1.99)			
Friend Death(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

t statistics in parentheses

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 II.6 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.

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. Parents should exhibit a more pronounced bequest motive compared to non-parents and therefore react less to a shock to mortality beliefs.

Table II.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 4.7 percentage points which is highly statistically significant at the 1 percent level. Conversely, parents reduce their saving rate, on average, by only 1.5 percentage point which is less than half of the effect size of childless individuals. This disparity indicates that households consider bequest motives in their response to a close friend dying which suggests

Table II.7: This table shows the results of regressing the saving rate on the death of a close friend indicator variable splitting 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.

	Saving Rate		Saving Rate	
	Parent	Childless	Child not in HH	Child in HH
Friend Death	-0.015***	-0.047***	-0.015**	0.002
	(-3.16)	(-4.74)	(-2.25)	(0.36)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	73,012	23,241	35,132	37,261
Adjusted R^2	0.454	0.507	0.458	0.432

t statistics in parentheses

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 1.5 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 demonstrate that the shock works through the intended channel. 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 which in turn translate into a lower saving rate. In the next section, I test further predictions that arise from the experience-based learning model.

4.4 Additional Predictions of the Model

After establishing a significant link between subjective 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 allows me to test two predictions how the shock to mortality beliefs should affect the saving rate. First, younger individuals should be more strongly affected by the shock than older individuals. Second, the life-cycle consumption model predicts a stronger impact of mortality beliefs for less risk-averse individuals.

The Role of 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. Furthermore, younger individuals on average have younger friends. The causes of death of younger individuals tend to be suicides, crimes, and accidents (c.f. Online Appendix) which cannot be anticipated. This should result in a more sharp updating of beliefs.

Hence, I split the sample along the median adult age of 50 and regress the saving rate on the death of a close friend indicator variable for each of the subsamples separately. Columns 1 of table II.8 exhibits the results for the younger households whereas columns 2 display the results for the older households. Columns 1 and 2 reveal that the shock reduces the saving rate of older households by only 1.2 percentage points whereas the impact on younger households is three times as large at 3.5 percentage points. The coefficients are statistically significant at the 5 percent and 1 percent level, respectively.

In conclusion, these findings are consistent with two not necessarily mutually exclusive explanations. On the one hand, the shock represents a larger part of younger individuals' set of experience. On the other hand, the shock is more surprising for younger individuals

Table II.8: This table shows the results of regressing the saving rate on an indicator variable equal to one for each period following the death of a close friend splitting households along age and risk aversion. Columns 1 and 2 display the results for households younger and older than 50, respectively. Columns 3 and 4 present the findings for high and low risk aversion households, respectively. I estimate OLS regressions with household and age fixed effects. Standard errors are clustered on the household level, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Saving Rate			
	Age < 50	Age > 50	High ρ	Low ρ
Friend Death	-0.035***	-0.012**	-0.012*	-0.032***
	(-5.47)	(-2.14)	(-1.89)	(-3.33)
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	49,617	48,870	31,875	18,660
Adjusted R^2	0.458	0.469	0.459	0.456

t statistics in parentheses

as their friends tend to be younger and experience non-natural causes of death. Hence, the shock would induce a stronger emotional reaction. Yet, both explanations would be consistent with the predictions of the experience-based learning model of Malmendier (2021).

Risk Aversion

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

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

One parameter that crucially determines the size of the effect of a shock to mortality beliefs on consumption is the risk aversion ρ. Everything else equal, households with lower risk aversion should increase their consumption more. Intuitively, high 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 the long-term impact of a friend's death on a household's saving decisions.

Column 3 of table II.8 shows that the high risk aversion households reduce their saving rate in response to the shock by 1.2 percentage points which is only statistically significant at the 10 percent level. Conversely, column 4 reveals that the low risk aversion households reduce their saving rate about three times as much by 3.2 percentage points which is highly significant at the 1 percent level. Overall, these findings are consistent with the predictions of the life-cycle model. High risk aversion households react less strongly to the increase in survival risk compared to low risk-aversion households. This is further evidence that the shock affects saving behavior through the channel of mortality beliefs.

5 Structural Estimation

In the final part of this paper, I structurally estimate the reduction in expected survival rate implied by the saving rate response and the parameter λ that governs how fast the personal experience fades out of the set of experiences relevant for the belief formation process.

5.1 Empirical Saving Rate Response

In a first step, I revisit the dynamics of the reduction in saving rate around the death of a close friend. One issue with the previous estimation of the dynamics around the shock might be that the post event period is contaminated by further shocks like another death of a close friend, or entering or exiting the work force. Moreover, I require for the structural estimation the reduction in saving rate following the shock compared to the average previous saving rate of a household rather than compared to untreated households. Hence, I create a sample of treated households that are between 25 and 65 years old. 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. On top of that, I require that at least the first 5 years after the shock are not missing. Then, I estimate the following regression model for this sample:

$$S_{it} = \sum_{k=-6}^{k=7} \beta_k FD_{i,k} + \gamma_t \times \tau_t + \epsilon_{it} \tag{10}$$

where $FD_{i,k}$ is an indicator variable equal to one in period k relative to the death of a close friend, γ_t are age fixed effects, and τ_t are year fixed effects. I include age times year fixed effects to average out age and cohort effects. Importantly, this estimation differs from table II.2 as it does not compare the reduction in saving rate of the treated households to the untreated households. In this regression, I compare the reduction in saving rate around the shock to the saving rate outside of the event window.

Figure II.5: This figure shows the reduction in saving rate around the death of a close friend. 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.

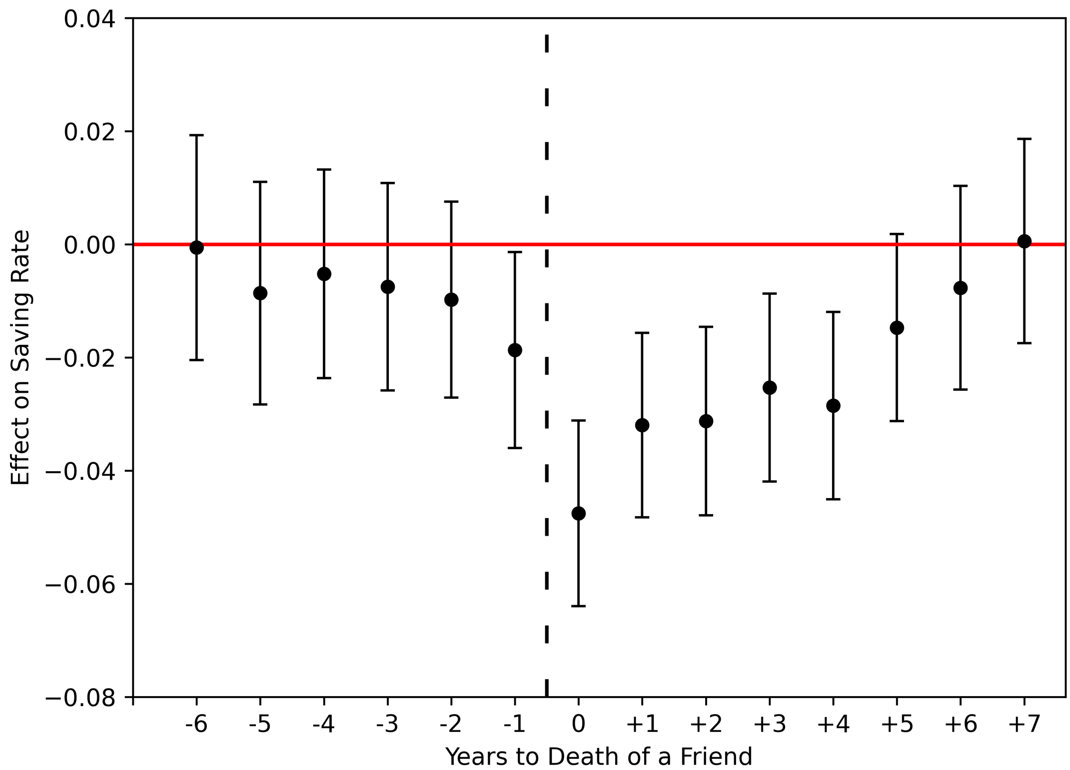


Figure II.5 displays the effect decay after the shock. The households strongly reduce their saving rate following the shock. This initial reaction attenuates back to zero over the following 6 years. This result is in line with the experience-based learning model which predicts that the personal experience gets less weight in the belief formation process as it moves farther into the past. The experience fades out of memory as there are no new experiences. In the next section, I use these reductions in saving rate to back out the model implied associated reduction in expected survival probability. Based on these changes in expected survival probabilities over the event window, I estimate the decay parameter λ which governs the shape of the weighting function in the belief formation process.

5.2 Estimation Problem

There are two parameters of interest I cannot observe in the data: the actual reduction in expected survival rate induced by the shock and the decay parameter λ. In a first step, I estimate the implied reduction in survival rate associated with the estimated coefficients in figure II.5. I can back out the implied drop in expected survival rate consistent with the observed impact on the saving rate using the model set up in part 2. Hence, I minimize the absolute difference between the relative reduction in saving rate estimated in that figure and the relative reduction in saving rate given a reduction in survival rate in the life-cycle model simulations.

$$\min_{\Delta s_{e+1}} \quad | \ \Delta S_e(\Delta s_{e+1}) - \Delta \hat{S}_e \ | \tag{11}$$

where $\Delta \hat{S}_e$ is the relative reduction in saving rate estimated in figure II.5 for event time e and $\Delta S_e(\Delta s_{e+1})$ is the relative reduction in saving rate given the reduction in expected survival rate Δs_{e+1} implied by model simulations, where s_{e+1} is the subjective probability of surviving to period $e + 1$.

The coefficients of figure II.5 represent the average reduction in saving rate following the death of a close friend across the sample. Moreover, these coefficients are net of age and cohort effects as the regression model includes age times year fixed effects. Hence, when simulating the shock to expected survival probabilities in the life-cycle model I assign it to the age of 49 which is roughly the average age at which the death of a close friend occurs in my sample. One assumption I have to make for this analysis concerns the agents' expectations about the survival probability $\Gamma(a, X)$ before the shock. I assume that previous to the shock 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).

Table II.9: This table shows the parameter values for solving the life-cycle consumption model for the structural estimation. 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	t_R	65
Maximum life span	T	100
Risk aversion	ρ	2 - 5
Discount factor	β	0.96
Financial market		
Risk-free rate	R_f	1.02
Labor income		
Effect of $age/10$ on log wage	θ_1	-0.022
Effect of $age^2/100$ on log wage	θ_2	0.059
Effect of $age^3/1000$ on log wage	θ_3	-0.008
Constant	θ_0	9.664
Replacement rate in retirement		0.54
Standard deviation persistent income shock	σ_ζ	0.129
Standard deviation transitory income shock	σ_ϵ	0.112

In a second step, I estimate the decay parameter λ which optimally fits the weighting function through the implied reduction in survival rates. This is possible by recognizing that the change in expected survival rate is given by:

$$\Delta E[s_t] = \left[\Gamma_t(a, X) + \sum_{k=0}^{t} w(\lambda, k, t) M_{t-k}\right] - \left[\Gamma_{t-1}(a, X) + \sum_{k=0}^{t-1} w(\lambda, k, t-1) M_{t-k}\right] \quad (12)$$

It is crucial to recognize that in the first period following the shock the new experience receives a weight of 1 in the set of experiences as it is the only relevant experience in this domain. Moreover, by the construction of my sample, the agents do not experience further shocks in all following periods. Hence, all following $M_{t\neq k}$ are equal to zero:

$$\Delta E[s_t] = \Gamma_t(a, X) - \Gamma_{t-1}(a, X) + (w(\lambda, k, t) - w(\lambda, k, t-1))M_0 \tag{13}$$

The change in objective survival probability $\Gamma_t(a, X) - \Gamma_{t-1}(a, X)$ is close to zero from one period to the next. Hence, I am left with:

$$\Delta E[s_t] = (w(\lambda, k, t) - w(\lambda, k, t-1))M_0 \tag{14}$$

where M_0 is the initial reduction in expected survival rate following the shock. Thus, the change in weights is just equal to the change in survival rate divided by the initial reduction in expected survival rate. Given that I estimate the implied reduction in expected survival rate in the first step of the estimation procedure and the initial weight of the experience is equal to 1, it is straightforward to calculate the weights implied by the empirical reduction in expected survival probability. Finally, this allows me to estimate the decay parameter λ that minimizes the squared difference between the implied weights by the empirical results and the theoretical weights:

$$\min_{\lambda} \; (\mathbf{w}(t, \lambda, e) - \hat{\mathbf{w}}(t, e))'(\mathbf{w}(t, \lambda, e) - \hat{\mathbf{w}}(t, e)) \quad \forall\, t = e \in [0, 7] \tag{15}$$

where $\hat{\mathbf{w}}$ is the vector of weights of the t-periods ago event from the relative reduction in Δs_{e+1} estimated from formula (11) and $\mathbf{w}$ is the vector of weights implied by the above formula for a given λ. For details regarding the exact estimation process, please refer to appendix B3.

5.3 Results

Table II.10 shows the reduction in expected survival rate implied by the empirically observed reduction in saving rate in the 6 years following the shock. As mentioned in section 4.3.1 the agent's reaction to the shock strongly depends on her risk aversion ρ. Hence, I estimate the reduction in expected survival probability for a range of reasonable risk aversion specifications.

Table II.10: 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 coefficient of risk aversion ρ ranging from 2 to 5. The final row shows the fitted decay parameter λ.

	$\rho = 2$	$\rho = 3$	$\rho = 4$	$\rho = 5$
Period 0	-0.037	-0.067	-0.101	-0.136
Period 1	-0.026	-0.046	-0.068	-0.091
Period 2	-0.025	-0.044	-0.064	-0.086
Period 3	-0.021	-0.035	-0.052	-0.069
Period 4	-0.024	-0.039	-0.057	-0.076
Period 5	-0.014	-0.021	-0.030	-0.040
Period 6	-0.001	-0.001	-0.001	-0.001
λ	**1.15**	**1.31**	**1.37**	**1.39**

Depending on the level of risk aversion, the initial reduction in expected survival probability implied by the observed reduction in saving rate ranges from 1.2 percent to 13.6 percent. Even at a reasonable level of risk aversion of 3 (Chetty, 2006), the observed reduction in saving rate implies a reduction of survival probability of 6.7 percent. In the next year, the relative reduction in expected survival probability is still at 4.6 percent. Over the following five years, this initial reduction in survival probability attenuates to zero. These effects are considerable given that the objective survival probability at age 49 is 99.79 percentage points. Hence, a reduction of 6.7 percent suggests that the expected survival rate drops to 93.1 percentage points directly following the shock.

Next, the last row in table II.10 displays the decay parameter λ associated with the attenuating reaction to the shock. The findings show that the estimated λ does not strongly depend on the agent's risk aversion. This is not surprising as it estimated from the changes in expected survival probability from one period to the next rather than from levels. The coefficient estimates range from 1.1 to 1.3. This λ estimate is in the range of the estimates of Malmendier and Nagel (2011) which lie between 1.3 and 1.9. In conclusion, my estimations reveal that the personal experience of the death of a close friend has a quantitatively large impact on a household's mortality beliefs. This is surprising given the non-material nature of the shock. On top of that, the weighting function that governs how this personal experience is incorporated into the belief formation process over time exhibits a similar shape as Malmendier and Nagel (2011). This finding is interesting as my paper explores the completely different domain of mortality beliefs as it suggests that there might be a rate at which individuals "forget" about past experiences that is independent of domains.

6 Robustness

In this section, I address three potential concerns that could explain the observed reduction in saving rate following the death of a close friend. These alternative mechanisms are related to the shock but do not work through the channel of mortality beliefs becoming more pessimistic. Households could take some drastic life choices that affect the composition or work situation of their household. Building on that, there might be unobserved events induced by the shock that lead to a drastic reduction in income which then mechanically reduces the saving rate as consumption might be sticky. Finally, the shock might affect their mental health negatively which micht affect their preferences.

6.1 Life-changing Events

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 regress a dummy variable that indicates a child birth in the previous year on the shock dummy lagged by 1 year to account for the 9 months a pregnancy takes. Similarly, I regress the child birth dummy on an indicator variable equal to one in all periods following the shock. Column 1 and 2 in table II.11 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.

Table II.11: This table explores the impact of the death of a close friend on various life choices. Column 1, 3, and 5 regress a birth of a child indicator variable, change in occupation indicator variable, and hours worked on a indicator variable equal to one in the next year following the shock. Conversely, columns 2, 4, and 6 regress the aforementioned life choices on an indicator variable equal to one in all periods following the death of a close friend. I estimate OLS regressions with person and age fixed effects. Standard errors are clustered on the individual 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
Friend Death		-0.001		0.002		-0.073
		(-0.74)		(0.41)		(-0.47)
Friend Death(t)			-0.003		0.059	
			(-0.73)		(0.58)	
Friend Death(t-1)	-0.002**					
	(-2.14)					
Person FE	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES
Observations	196,760	237,556	139,533	154,331	150,163	165,449
Adjusted R^2	0.110	0.102	0.146	0.146	0.630	0.624

t statistics in parentheses

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 II.11 I regress a dummy indicating a change in occupation on the death of a friend dummy equal to one either in the period immediately following the shock (column 3) or in all periods following the shock (column 4). 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 shock. Thus in columns 5 and 6, I regress the individual's working hours on the shock dummy equal to one either in the period immediately following the shock (column 5) or in all periods following the shock (column 6). However, the hours worked only decrease on average by 0.07 in the long run 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.

6.2 Changes in Income

In this section, I go a step further and demonstrate that the reduction in survival rate does not purely depend on a reduction in incoming following the shock. For that purpose, I repeat the analyses of table II.2 while controlling for income changes. On top of that, I consuct the same analyses for a subset of households who experience a non-negative change in income in the next one, two, three, or four years following the death of a close friend.

Table II.12: This table shows the results of regressing the saving rate on an indicator variable equal to one in each period following the death of a close friend for a subsample of households that experience a positive change in income in the next 1, 2, 3, or 4 years following the shock in columns 2 to 5. 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.

	Saving Rate				
	Saving Rate	Next year	Next 2 years	Next 3 years	Next 4 years
Friend Death	-0.020***	-0.006	-0.010**	-0.011**	-0.010**
	(-4.68)	(-1.29)	(-2.11)	(-2.43)	(-2.26)
Δ Income	1.044***				
	(27.26)				
Household FE	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES
Observations	89,571	84,724	86,940	88,299	88,630
Adjusted R^2	0.534	0.461	0.466	0.464	0.462

t statistics in parentheses

Table II.12 displays the results of this analysis. Column 1 demonstrates that controlling for changes in income barely reduces the coefficient of interest to 2 percentage points. Next, I run the most restrictive possible test and limit my sample to a subset of households that experience non-negative income shocks following the death of a close friend. Indeed, the impact of the shock is reduced considerably but remains robustly at around 1 percentage point. Furthermore, the coefficients remain statistically significant at the 5 percent level even for this selected sample. Overall, this robustness test shows that the lower saving rate following the shock still persists even after restricting the treated group to a subsample of households that experiences positive income changes following the shock. Moreover, in the context of the standard consumption-saving model it is unclear whether one should restrict the sample as households choose their optimal consumption level and saving rate given their wealth and income.

6.3 Physical and Mental Health

Some research in health economics suggests that individuals might change their preferences in response to a deterioration in mental health (Bogan & Fertig, 2013; Choung et al., 2022). As the death of a close friend most likely negatively affects one's mental this might affect her preferences and thereby reduce the saving rate through a different channel than distorted mortality beliefs.

In columns 1 and 2 of table II.13, I explore the impact of the shock on the saving rate while explicitly controlling for a household's general and mental health. Clearly, these controls do not change the magnitude of the impact of the shock on the saving rate. The death of a close friend reduces the saving rate, on average, by 2.3 percentage points which is highly significant at the 1 percent level.

Furthermore, to make sure that the observed impact of the shock is not driven by mental health induced changes in preferences, I restrict the analysis to households that experience a non-negative change in mental health in the one or two years following the shock. The results of this analysis are shown in column 3 and 4 of table II.13. Even though I exclude every household that experiences a negative change in mental health, the impact of the shock on the saving rate is barely affected. The shock reduces the

Table II.13: This table shows the results of regressing saving rate on an indicator variable that is equal to one in each period following the death of a close friend while controlling for a household's health. Column 1 and 2 show the results while controlling for general health and mental health, respectively. In columns 3 and 4, I require that the treated households experience a non-negative change in mental health in the following and the following two years. 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.

	Saving Rate	Saving Rate	1 year pos. Δmental health	2 year pos. Δmental health
Friend Death	-0.023***	-0.023***	-0.019***	-0.023***
	(-5.58)	(-5.55)	(-3.78)	(-4.49)
General Health	0.027***			
	(3.33)			
Mental Health		0.047***		
		(5.69)		
Household FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Observations	88,384	88,896	86,980	87,982
Adjusted R^2	0.460	0.460	0.462	0.460

t statistics in parentheses

saving rate by 1.8 and 2.3 percentage points, respectively.

Overall, these findings demonstrate that the reduction in saving rate is not driven by a change in households' preferences in response to a deterioration in mental health. This result further strengthens the idea that observed effect is caused by a change in households' mortality beliefs.

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 cannot be explained by adverse health outcomes, bequests, or drastic lifestyle changes. Furthermore, I augment the canonical life-cycle model of consumption by the experience-based learning model of Malmendier et al. (2020). Based on this theoretical framework, I quantify the impact of the shock on beliefs as well es structurally estimate the associated parameter λ that governs how fast the experience fades out of memory. I find that even though the shock has no impact on the household's material situation, it massively affects a household's mortality beliefs. Moreover, the decay parameter λ is in line with previous estimates.

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. Moreover, my paper demonstrates the importance of personal experiences in forming beliefs as even a non-material shock like the death of a close friend has a substantial impact on beliefs.

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 quantify 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. This suggests that life-time experiences can distort the financial decision-making of large parts of the population. The importance of personal experiences in forming beliefs might even exacerbate inequalities. One could imagine a situation where individuals of lower socioeconomic status are more often affected by negative experiences like becoming unemployed which translates into more pessimistic beliefs and even less optimal financial decision making.

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A Variable Description

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	Which of the following statements comes closest to describing your (and your family's) saving habits? *1 Don't save: usually spend more than income* *2 Don't save: usually spend about as much as income* *3 Save whatever is left over - no regular plan* *4 Spend regular income, save other income* *5 Save regularly by putting money aside each month*
Saving horizon	In planning your saving and spending, which of the following time periods is most important to you ? *1 The next week* *2 The next few months* *3 The next year* *4 The next 2 to 4 years* *5 The next 5 to 10 years* *6 More than 10 years ahead*
Fun expenditure	Sum of non-durable expenditure on leisure related categories (c.f. table II.5) divided by income.
Necessities expenditure	Sum of non-durable expenditure on necessity related categories (c.f. table II.5) divided by income.
Health expenditure	Sum of non-durable expenditure on health and insurance related categories (c.f. table II.5) divided by income.

Friend Death(t)	Indicator variable equal to one if the individual reports the death of a close friend in period t, and zero otherwise.
Friend Death	Indicator variable equal to one for each period following the death of a close friend, 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*

B Model and Estimation Details

B.1 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:

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

where c_{it} is the consumption of agent i at age t, β 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 ϵ_{it} is an idiosyncratic shock to labor income which is distributed $N(0, \sigma_\epsilon^2)$. ζ_{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 ϵ_{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.

B.2 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[4].

B.3 Structural Estimation

I estimate the implied reduction in survival rate and the associated decay parameter λ 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.

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 Figure II.5. 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 2 to 5. In a second step, I estimate the λ 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 λ 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 λ. Finally, I make sure this represents a global minimum.

[4]For setting up and solving the model, I utilize the *Heterogeneous Agents Resources and toolKit (HARK)* by Carroll et al. (2018)

Chapter III

Distorted Unemployment Beliefs and Stock Market Participation

Abstract

I find that households severely overestimate their future unemployment probability. I argue that this distorted perception of labor income risk significantly reduces households' stock investments. In reduced form regressions, I demonstrate that unemployment beliefs are highly predictive of actual unemployment shocks and significantly reduce households' risky share. Next, I structurally estimate a life-cycle model of portfolio choice that incorporates the empirical distortion in unemployment beliefs. The model matches the evolution of wealth, equity share and participation rates with more plausible risk aversion estimates than the model with objective beliefs. I find that distorted unemployment beliefs can explain low stock market investment rates especially among middle aged and less wealthy households.

1 Introduction

Most households around the world invest little to none of their wealth in stocks. Given the large equity premium, life-cycle models of consumption and saving struggle to explain why households are reluctant to invest in stocks. Yet, these low stock market investment rates are problematic as households forego large lifetime utility gains by hampering their wealth accumulation until retirement. Hence, they might face severe shortcomings in retirement income. In this paper, I argue that households hold distorted unemployment beliefs which reduces their willingness to invest into stocks.

From a theoretical point of view, labor income risk should be one of the most important factors determining stock market investment. If an individual is confronted with uninsurable labor income risk, this additional source of risk crowds out asset allocation risk (Gomes et al., 2021). From an empirical point of view, labor income risk is also one of the most import factors for financial decision making. In a recent survey, 64.8% of individuals report that labor income risk is important in determining their risky share (J. Choi & Robertson, 2020). Yet, it is difficult to reconcile empirically observed levels of labor income risk with stock market participation rates. However, most previous studies consider *objective* labor income risk in this context, whereas my paper explores how *subjective* labor income risk affects the decision to invest into the stock market.

Figure III.1 summarizes the main empirical finding of this paper. It plots the average reported unemployment beliefs of individuals versus the ex-post observed probability of entering unemployment. Clearly, individuals persistently overestimate the probability of losing their job within the next 12 months. I find this belief distortion in four large household panels and for a time span of over 20 years. I argue that the distortion in perceived labor income risk significantly contributes to the low stock market investment rates of households. Unemployment represents an extreme case of labor income risk as households cannot perfectly insure themselves against this income shock. The perception of excessive, uninsurable labor income risk intuitively reduces an individual's willingness to take on other forms of risks. Therefore, they shift their savings from the risky to the

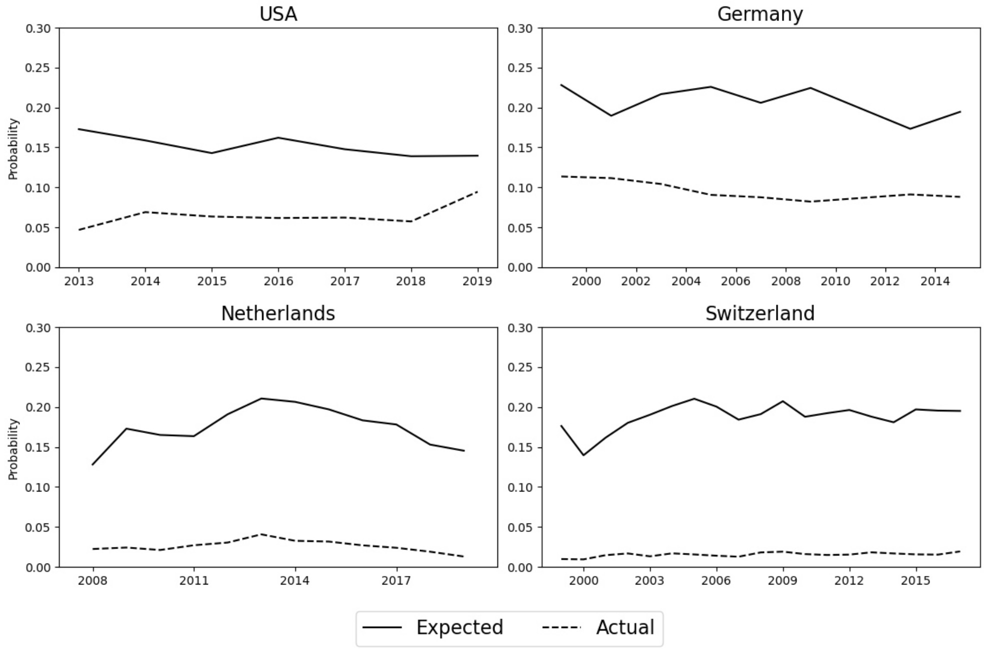

Figure III.1: Unemployment beliefs versus actual unemployment outcomes.

risk-free asset to reasonably maintain their level of consumption if the unemployment shock materializes.

In this paper, I establish three facts concerning elicited unemployment beliefs. First, individuals severely overestimate the likelihood of losing their job in the future. On average, survey participants report probabilities of losing their job within the next year of for example 15.5 percent in the USA or 17.6 percent in the Netherlands. This estimate strongly contrasts with the actual probability of losing their job of 6.7 percent and 2.6 percent, respectively. Yet, cross-sectional sample splits reveal that these elicited beliefs do correspond directionally to the objective probabilities. Focusing on the results for the USA, the subjective job loss likelihood decreases monotonically across income quintiles or educational attainment which is in line with the actual probabilities. Similarly, female participants report slightly higher unemployment beliefs than males which again is in line with actual outcomes.

Second, unemployment beliefs are highly persistent both at an aggregate level as well as at an individual level. At an aggregate level, Figure III.1 demonstrates that average unemployment beliefs only vary at most 5 percentage points from year to year for all countries. This represents a maximum relative change of 20 to 25 percent. On an individual level, the transition matrix of unemployment beliefs from one period to the next reveals that most individuals correctly report a 0 to 10 percent job loss likelihood. Nevertheless, if a participant reports a very high probability in one period, she reverts back to a low job loss probability in the next period most of the time.

Third, the reported probability of losing one's job is highly predictive of the actual probability of job loss both at the extensive as well as the intensive margin. I find that a one standard deviation increase in perceived job loss likelihood relates at the extensive margin to an increase in the probability of actually losing one's job by 4.9 percentage points in the USA, 8.0 percentage points in Germany, 1.5 percentage points in Switzerland, and 4.1 percentage points in the Netherlands. Comparing these coefficients with the baseline probability of losing one's job in each of these countries reveals an economically highly significant effect. A one standard deviation increase in perceived job loss likelihood increases the actual probability of job loss by 75 to around 100 percent. Including person fixed effects does not alter the statistical and economical significance of the results which shows that reported unemployment beliefs are even within-person highly predictive of future outcomes. Overall, these results suggest that elicited unemployment beliefs contain private information about personal labor income risk.

On top of that, I demonstrate in reduced form regressions that households indeed consider unemployment beliefs for their portfolio allocation decision. On average, a one standard deviation increase in unemployment beliefs reduces the risky share by 1 percentage point and the conditional risky share by 2.2 percentage points. Considering that the average risky share is 8.3 percent and the conditional risky share is around 25 percent, the effect size is substantial. Thus, individuals consider unemployment beliefs in their financial decision making. In conclusion, I find that the discrepancy of subjective and actual unemployment beliefs is highly stable and subjective unemployment beliefs are predictive of investment in the risky share.

I explore the implications of this novel finding for the standard theoretical model of stock market participation. I set up a rich life-cycle model of consumption and saving in a risky and risk-free asset and target the empirically observed evolution of wealth, stock market participation, and risky share over an agent's life-cycle to structurally estimate the unobserved parameters like relative risk aversion, discount factor, and participation cost. I calibrate unemployment beliefs to survey responses and incorporate them into my model. I find that the augmented model fits the observed empirical moments with significantly more plausible parameter combinations compared to the model with objective unemployment beliefs.

In the baseline model with objective beliefs, the structural estimation reveals a coefficient of relative risk aversion of 12.739, a discount factor of 0.623, and a per period fixed participation cost of 1.7 percent. Conversely, incorporating distorted beliefs reduces the risk aversion to 7.792 and increases the discount factor to 0.719 while reducing the required participation cost to 1.5 percent. This vast reduction in required risk aversion is remarkable considering that only the beliefs of the agents have changed. Agents still face the objective probability of losing their job. Hence, the likelihood of experiencing this disaster labor income shock namely unemployment is relatively low. This suggests that life-cycle models of consumption can greatly benefit from incorporating beliefs elicited from surveys.

In the final part of the paper, I explore further how distorted unemployment beliefs help to calibrate the model to the data with more reasonable parameter values. For that purpose, I plot the agent's policy functions for the optimal risky share depending on her wealth-to-earnings ratio. In the classic life-cycle model of consumption and saving, the relationship between the risky share and wealth-to-earnings is downward sloping. Intuitively, labor income has bond like properties. Hence, agents with a higher share of labor income in future wealth should invest more in stocks. However, empirically one observes a flat relationship between the risky share and wealth-to-earnings ratio. Introducing distorted unemployment beliefs in the model resolves this discrepancy between theory and empirics. The increase in perceived riskiness of labor income makes labor income more stock like and thereby reduces the risky share for households with low wealth-to-earnings ratios. Hence, the policy function becomes flat which, in line with empirical findings, reduces the optimal risky share for less wealthy households.

Furthermore, plotting the policy functions for agents at various ages reveals that distorted unemployment beliefs have the largest impact on the risky share for middle aged households. In conjunction with the finding that agents at moderate wealth-to-earnings ratios are affected the most by pessimistic unemployment beliefs, these results explain how the risky share over the life-cycle becomes monotonically upwards sloping in a model that considers distorted unemployment beliefs. Middle aged households with moderate wealth would invest most of their wealth in stocks in the model with objective beliefs. The increasing risky share over the life-cycle is in line with the empirically observed life-cycle moments but contrasts with the decreasing risky share suggested by the classic life-cycle model like introduced by Cocco, Gomes, and Maenhout (2005). Hence, the model with distorted unemployment beliefs requires significantly lower levels of risk aversion to fit the low stock market investment rates observed in the data.

My paper mainly relates to two strands of the finance literature. First, I contribute to the scarce literature in finance on unemployment beliefs. There are only a few papers that look explicitly at the unemployment beliefs elicited in surveys. Notably, Dickerson and Green (2012) and Kuchler and Zafar (2019) find that unemployment beliefs are highly predictive of actual job losses. This is in line with my results for a broader set of countries. On top of that, Stephens Jr (2004) and Pettinicchi and Vellekoop (2019) link elicited unemployment beliefs to future consumption. Intuitively, higher job uncertainty leads to a more pronounced precautionary saving motive and thereby reduced consumption. In this paper, I go beyond empirical analyses surrounding relative changes in unemployment beliefs and argue that the reported values represent elicited beliefs. I explicitly include this distortion in the standard theoretical model and explore the ability of the augmented model to fit the empirical data.

Second, I closely relate to the literature that attempts to match the life-cycle model of consumption and saving to the empirically observed evolution of wealth and stock market investment. The main issue is to match low stock market participation rates and the initially low but increasing risky share over the life-cycle (e.g. Mankiw & Zeldes, 1991; Haliassos & Bertaut, 1995; Ameriks & Zeldes, 2004). The literature has proposed several solutions to this problem based on the seminal paper by Cocco et al. (2005). Some papers introduce a fixed stock market entry cost (Alan, 2006; Gomes & Michaelides, 2005) or a fixed per period participation cost (Vissing-Jorgensen, 2002). Others argue that the risky share drops if labor income and stock returns are cointegrated (Benzoni et al., 2007; Storesletten et al., 2007; Lynch & Tan, 2011). Catherine (2022) expands on that idea by introducing a correlation between the skewness of labor income and stock market crashes. Finally, the literature suggests infrequent large stock market crashes (Fagereng et al., 2017) or non-standard preferences (Polkovnichenko, 2007; Gomes & Michaelides, 2005) to match the empirical life-cycle profiles.

I add to this literature by introducing subjective beliefs into the model which are directly elicited from survey micro data. I augment the seminal model by a component that is shown in the data to affect households' financial decision making. Hence, households actually consider these unemployment beliefs when taking decisions related to portfolio choice. Importantly, I only change an agent's beliefs not the actual outcomes. There little research so far that has considered subjective beliefs founded in survey data in the context of the consumption-saving model[1].

This paper is structured as follows. In section 2, I explore elicited unemployment beliefs from four large household panels around the world. I present descriptive statistics and link unemployment beliefs to subsequent investment decisions. Section 3 introduces the theoretical model and section 4 describes the calibration of the model and the structural estimation procedure. Section 5 discusses the findings of the structural estimation and section 6 explores the underlying drivers of the model fit. Section 7 concludes.

[1]Notable exceptions are Heimer, Myrseth, and Schoenle (2019) in the context of mortality beliefs and Rozsypal and Schlafmann (2023) for labor income growth.

2 Unemployment Beliefs in the Data

2.1 Data

In this section, I describe the micro data on unemployment beliefs. The data on unemployment, unemployment beliefs, and demographics come from four large household panels. First, the data for the USA stems from the Survey of Consumer Expectations (SCE) administered by the Federal Reserve Bank. This survey asks a nationally representative sample of around 1,300 household heads each month about their economic beliefs. Each respondent stays in the panel for 12 months before she is rotated out of the survey. Second, I utilize the German Socio-Economic Panel (GSOEP) for the German data. The GSOEP is one of the most long-running and comprehensive household panels worldwide starting in 1984 and covering around 15,000 households. Third, the data for the Netherlands comes from the Longitudinal Internet studies for the Social Sciences (LISS). This household panel started in 2007 and surveys around 5,000 households each year. Finally, I utilize the Swiss Household Panel (SHP) for Switzerland. The SHP begins in 1999 and interviews roughly 5,000 households every year. Each of the household panels aims to survey a nationally representative sample of adults typically starting at the age of 16.

Table III.1 shows the descriptive statistics for the four household panels. As each of these surveys covers a representative sample of the respective population, roughly half of the sample is female and the average age is 50. The net income of households is reported in local currency and differs significantly across countries due to differing levels of consumer prices. Next, I categorize the highest educational degree individuals obtained into the three categories: no degree (equivalent to a high school degree), vocational training received, and university related education. There are large differences across countries mostly reflecting institutional differences. Germany and Switzerland traditionally have strong vocational systems whereas in the USA the emphasis lies on college education. Across countries, around 60 percent of the population are employed. Unemployment rates differ significantly from country to country ranging from a little over 1 percent in

Switzerland to around 9 percent in the USA. Thus, the averages for education and unemployment rates need to be compared cautiously across countries as they heavily depend on the institutional setting, varying sample periods, and differing definitions of survey items.

The main variable of interest for this paper is an individual's unemployment beliefs. I elicit these with variations of the question *What do you think is the percent chance that you will lose your job during the next 12 months?*. The average stated perceived probability of job loss within the next year ranges from 15 percent in the USA to around 18 percent in the three other countries. Importantly, the numbers for Germany are not directly comparable as the GSOEP asks participants to forecast the likelihood of job loss within the next 2 years. Similarly, the SCE and LISS elicit unemployment beliefs on a probability scale whereas the SHP reports a discrete scale from 0 to 10. For details regarding the exact phrasing of these survey questions please refer to appendix A.

Furthermore, I utilize the employment status of individuals to compare it directly to

Table III.1: This table shows the summary statistics for the four households panels employed. Columns 1 and 2 display mean and standard deviation for the Survey of Consumer Expectations (SCE), columns 3 and 4 present the mean and standard deviation for the German Socioeconomic Panel (GSOEP), columns 5 and 6 show the mean and standard deviation for the Longitudinal internet studies for the social science (LISS), and columns 7 and 8 summarize the Swiss household panel (SHP).

	USA		Germany		Netherlands		Switzerland	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Demographics								
Female	0.49	0.50	0.52	0.50	0.51	0.50	0.52	0.50
Age	50.05	15.14	46.74	17.42	47.46	17.28	48.40	17.63
Net Income	.	.	1463	1252	1247	6096	4918	4942
Education								
No Degree	0.34	0.47	0.13	0.34	0.44	0.50	0.23	0.42
Vocational	0.13	0.34	0.57	0.50	0.24	0.43	0.40	0.49
University	0.53	0.50	0.19	0.40	0.32	0.47	0.37	0.48
Employment								
Employed	0.68	0.47	0.59	0.49	0.57	0.50	0.61	0.49
Unemployed	0.09	0.29	0.07	0.26	0.03	0.17	0.01	0.11
Jobloss								
Expectation	0.15	0.21	0.19	0.25	0.18	0.26	0.19	0.24
Actual	0.06	0.24	0.10	0.30	0.03	0.16	0.02	0.12

their unemployment beliefs. The actual probability of job loss is clearly lower than the perceived one. It ranges from 6 percent in the USA to only 2 percent in Switzerland. Furthermore, the 2 year probability of job loss in Germany is 10 percent. Overall, these numbers are in line with the less rigid labor market in the USA compared to the rather rigid labor markets in Europe. In the next sections, I further explore descriptive statistics regarding the elicited subjective unemployment beliefs and establish several empirical patterns that persist across countries and time with respect to these unemployment beliefs.

2.2 Average Unemployment Beliefs

In this part, I explore in more detail the large discrepancy between perceived unemployment beliefs and the actual job loss probability as well as the cross-sectional distribution of unemployment beliefs. Table III.2 shows the average unemployment beliefs and actual unemployment probability for the SCE, GSOEP, LISS, and SHP surveys. The perceived probability of becoming unemployed does not vary much across countries. It ranges from, on average, 15 percent in the US to 19 percent in Switzerland. Conversely, the actual probability of losing one's job within the corresponding time period varies between nearly zero in Switzerland to around 6 percent in the US.

Partly the cross-country variation reflect differences in employment protection legislation. Western Europe has stricter labor laws compared to the US, which in turn leads to lower forced job turnover. Moreover, the Swiss unemployment beliefs are very high which is probably caused by the different scaling they use when eliciting them. In the other panels, participants are asked about the actual probability of job loss or answer the question on a scale from "definitely not happen" to "definitely happen". Conversely, the scale in the Swiss panel ranges from "no risk at all" to "a real risk" which participants most likely do not interpret as an absolutely certain outcome.

Comparing reported unemployment beliefs and the actual probability of job loss reveals that reported unemployment beliefs are a lot larger than the actual probability of losing one's job across all countries. Focusing on the USA, the perceived probability of

Table III.2: This table shows the subjective and actual probability of losing one's job within one year (within 2 years for Germany). Furthermore, the samples are split along gender, age, education, and income. Columns 1 and 2 present the averages for the SCE, columns 3 and 4 for the GSOEP, columns 5 and 6 for the LISS, and columns 7 and 8 for the SHP.

	USA		Germany		Netherlands		Switzerland	
	Belief	Actual	Belief	Actual	Belief	Actual	Belief	Actual
Total	0.155	0.067	0.195	0.098	0.176	0.026	0.189	0.015
Male	0.153	0.056	0.192	0.108	0.167	0.025	0.189	0.013
Female	0.156	0.080	0.198	0.087	0.186	0.027	0.189	0.019
<35	0.136	0.078	0.235	0.165	0.158	0.030	0.189	0.028
35-50	0.152	0.061	0.193	0.105	0.180	0.024	0.202	0.014
>50	0.173	0.067	0.157	0.055	0.182	0.025	0.173	0.009
No Degree	0.165	0.080	0.210	0.097	0.196	0.030	0.173	0.018
Voc. Training	0.155	0.092	0.202	0.100	0.187	0.028	0.199	0.016
University	0.149	0.055	0.173	0.089	0.155	0.021	0.186	0.014
Lowest Income	0.207	0.117	0.230	0.208	0.195	0.025	0.182	0.034
2	0.165	0.069	0.245	0.180	0.221	0.042	0.206	0.032
3	0.138	0.056	0.204	0.117	0.224	0.034	0.205	0.021
4	0.132	0.035	0.170	0.081	0.191	0.032	0.190	0.013
Highest Income	0.136	0.037	0.125	0.056	0.152	0.019	0.166	0.007

unemployment (15.5 percent) is double the actual job loss likelihood (6.7 percent). This is a significant gap which should in theory have considerable impact on an individual's financial decision making as unemployment represents a large labor income shock. In consequence, individuals consume less and hold less of the risky asset. Overall, the discrepancy between subjective and objective unemployment beliefs is stable over time and across four developed countries. This is first evidence that the difference is not purely caused by noise in the survey data. Hence, it emerges the first fact surrounding unemployment beliefs from the micro data. Participants consistently overestimate the likelihood of job loss. This suggests that individuals hold distorted unemployment beliefs. In the remaining parts of the chapter, I am conducting some plausibility checks to ensure that this effect is not caused by individuals randomly answering this question because they do not know what a sensible answer would be.

Next, I explore how unemployment beliefs are distributed. Figure III.1 plots the distribution of subjective unemployment beliefs for each of the four surveys. In each of the countries around 40 percent of individuals report a zero percent probability of losing their job within the next 12 months. This percentage is slightly lower in the USA which is expected considering the less strict labor laws. Yet. there is considerable variation in the answers across the distribution with most participants reporting unemployment probabilities of less than 30 percent. As usual in surveys eliciting probability distributions, there is a slight spike in individuals reporting a job loss likelihood of 50 percent. However, the percentage of answers is less than 10 percent of the overall sample. Overall, the fact that most individuals report reasonably low unemployment probabilities further emphasizes that these reported probabilities contain information about participants' beliefs.

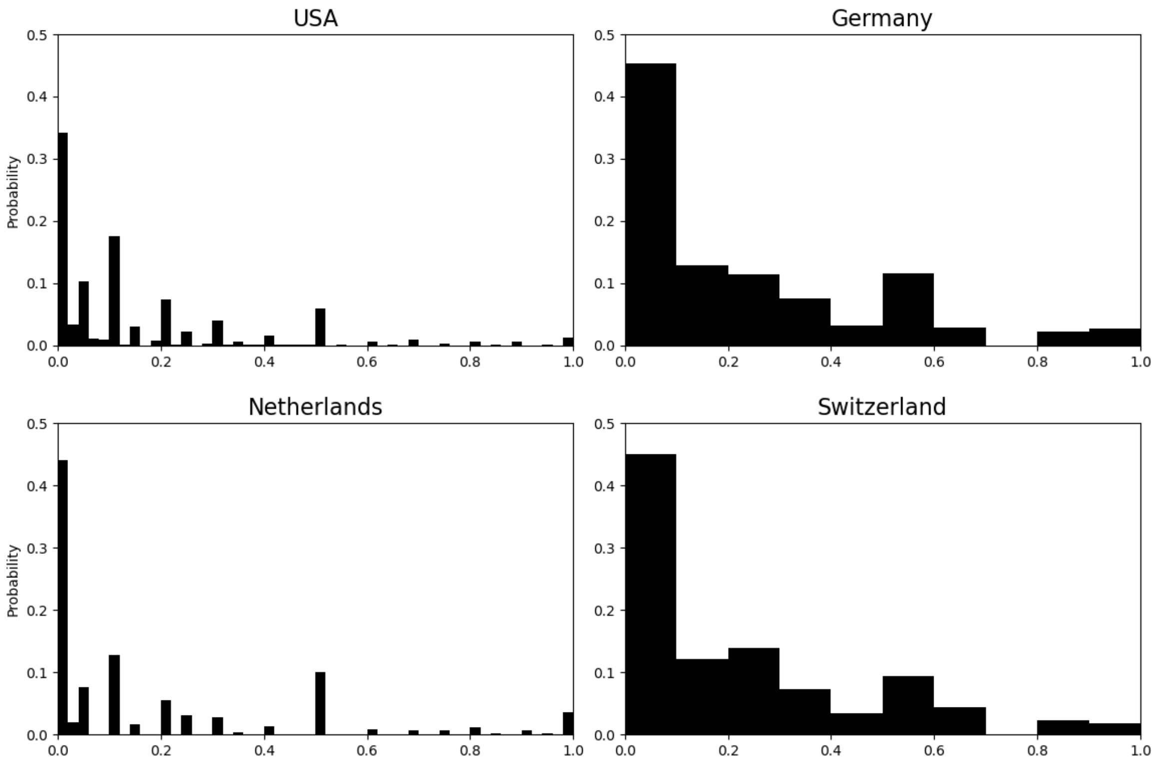

Figure III.1: This figure plots the distribution of stated unemployment beliefs for the SCE, GSOEP, LISS, and SHP. The subjective unemployment beliefs are elicited on a continuous scale for the SCE and LISS. Conversely, the answers for the GSOEP and SHP are on a discrete scale in steps of 0.1.

Table III.2 splits the country samples along various demographics and compares expected and actual job loss probabilities in the subsamples. This allows me to investigate whether there are systematic cross-sectional biases in perceived job loss likelihood across population groups. First, women and men do not appear to significantly differ in their reported unemployment beliefs, which is also in line with the difference of actual probability of losing their job. Second, the perceived probability of losing one's job strongly increases with age in the US and Netherlands, whereas it decreases in Germany. However, the actual probability does not vary much in the former two countries, whereas in Germany the actual probability strongly decreases which is in line with the perceived probability. Third, unemployment beliefs are becoming more optimistic with the level of education attained which is roughly in line with actual outcomes. For example, going from no degree to college degree drops the actual probability of unemployment by 2.5 percentage points. Similarly, the perceived job loss likelihood drops by 1.6 percentage points. The other countries exhibit similar patterns. Finally, splitting the samples into income quintiles reveals that the actual probability of losing one's job decreases by income across countries. The same pattern can be observed in the elicited unemployment beliefs. Individuals with the highest incomes report the lowest subjective likelihood of losing their job.

In conclusion, these results show that there is a large difference in the level of unemployment beliefs and the actual outcomes. However, cross-sectional sample splits show that across individuals the dispersion in unemployment beliefs is not purely noise. Groups of individuals with attributes associated with higher job loss likelihood also perceive the unemployment probability to be higher. Furthermore, most individuals report a near zero probability of job loss in line with actual outcomes. The question that arises is whether unemployment beliefs are also meaningful in the time-series. Fortunately, the panel structure of the surveys allows me to test the persistence of beliefs and whether unemployment beliefs are predictive of actual unemployment.

2.3 Persistence of Unemployment Beliefs

In this section, I explore the persistence of unemployment beliefs over time. Figure III.1 shows that beliefs do not vary significantly on an aggregate level. For example, in the USA average unemployment beliefs only vary 5 percentage points from one year to the next. Similar magnitudes can be observed in the other panels which are more long-running.

This suggests that the average level of unemployment beliefs is very persistent and that the discrepancy to actual outcomes is not caused by year to year noise in the data.

Next, I investigate the persistence of unemployment beliefs on an individual level. Table III.3 shows a transition matrix for bins of unemployment beliefs for the GSOEP, LISS, and SHP. Unfortunately, I cannot conduct these analyses using the SCE as it is a rotating panel. Hence, I only observe an individual in the SCE for at most one year. Reported job loss probabilities are sorted into 5 increasing bins with each bin representing a 20 percent unemployment probability step. Depending on the country, 73 to 85 percent of individuals report a probability of losing their job of less than 20 percent in the following year if they reported a less than 20 percent likelihood in the year before. Another, large portion of the population across panels reports a persistent unemployment probability of 20 to 40 percent from one period to the next.

Table III.3: This table shows how perceived unemployment beliefs change from one year to the next in the GSOEP, LISS, SHP. Unemployment beliefs are sorted into 5 bins increasing from 0 to 100 percent in steps of 20 percent. The rows represent last period's unemployment beliefs bin and the column this period's unemployment beliefs bin.

	Germany					Netherlands					Switzerland				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
1	0.73	0.15	0.08	0.01	0.03	0.85	0.05	0.05	0.01	0.03	0.76	0.14	0.05	0.02	0.02
2	0.35	0.37	0.20	0.04	0.04	0.49	0.24	0.19	0.04	0.04	0.36	0.42	0.15	0.04	0.03
3	0.24	0.26	0.37	0.06	0.07	0.32	0.12	0.42	0.05	0.08	0.23	0.26	0.35	0.10	0.06
4	0.24	0.22	0.33	0.10	0.10	0.37	0.14	0.26	0.10	0.13	0.20	0.22	0.30	0.18	0.10
5	0.33	0.20	0.24	0.07	0.16	0.54	0.05	0.17	0.05	0.19	0.30	0.17	0.21	0.11	0.21

However, unemployment beliefs tend to consistently revert back to low levels even after individuals report unemployment beliefs of over 80 percent. For example, 54 percent of individuals in the Netherlands that reported unemployment beliefs of above 80 percent state unemployment beliefs of less than 20 percent in the next year. Conversely, participants rarely jump to very high job loss probabilities following a period in which they expect their unemployment probability to be less than 20 percent. This finding suggest that individuals, on average, report high probabilities of unemployment in periods of high personal uncertainty but revert back to a near zero probability as soon as the situation has improved.

Table III.4: This table shows the results of regressing unemployment beliefs on past unemployment beliefs in the GSOEP, LISS, and SHP. In columns 1 and 2, I regress this years standardized unemployment beliefs on standardized unemployment beliefs stated two years ago. Conversely, in the remaining columns I regress this years standardized unemployment beliefs on last years standardized unemployment beliefs. Additionally, columns 2, 4, and 6 include year fixed effects. Standard errors are clustered by person level, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Germany		Netherlands		Switzerland	
	Unemp. Beliefs		Unemp. Beliefs		Unemp. Beliefs	
Unemp. Beliefs(t-2)	0.389***	0.391***				
	(68.51)	(68.49)				
Unemp. Beliefs(t-1)			0.466***	0.466***	0.416***	0.415***
			(83.78)	(83.61)	(36.15)	(35.93)
Year FE	NO	YES	NO	YES	NO	YES
Observations	50,353	50,353	76,147	76,147	18,199	18,199
Adjusted R^2	0.146	0.149	0.211	0.213	0.161	0.165

I confirm the results of the transition matrix in a regression context. Table III.4 shows the results of regressing this year's unemployment beliefs on unemployment beliefs reported in the previous year or report two years ago in the case of the GSOEP. The regressions demonstrate that a one standard deviation increase in the previously reported unemployment beliefs increases, on average, today's unemployment beliefs by around 40 to 50 percent. This coefficient is highly significant at the 1 percent level in all specifications both with and without year fixed effects. This demonstrates that past unemployment beliefs are highly predictive of future unemployment beliefs. Overall, if the rare jumps to high unemployment beliefs reveal private information, they should translate into actual outcomes. Hence, in the next section I test this hypothesis.

2.4 Unemployment Beliefs and Actual Unemployment

Next, I test whether unemployment beliefs on an individual level are predictive of actually experiencing unemployment. Hence, I regress an indicator variable equal to one if an individual loses his job within the year on the standardized perceived probability of losing her job within the next 12 months. Table III.5 displays the results of the analysis.

Table III.5: This table shows the results of regressing an indicator variable equal to one if one loses her job within one year on the perceived likelihood of losing one's job within the next year for various countries. The unemployment belief variable is standardized. Columns 1, 2, 4, and 6 include year fixed effects. Columns 3, 5, and 7 additionally include person fixed effects. Standard errors are clustered by person level, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	USA	Germany		Switzerland		Netherlands	
	Actual	Actual	Actual	Actual	Actual	Actual	Actual
Unemployment	0.049***	0.080***	0.061***	0.015***	0.015***	0.041***	0.033***
Beliefs	(12.14)	(54.93)	(29.75)	(17.67)	(14.05)	(19.42)	(13.89)
Person FE	NO	NO	YES	NO	YES	NO	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	8,867	87,301	73,980	72,181	69,577	26,182	24,312
Adjusted R^2	0.044	0.065	0.220	0.020	0.101	0.062	0.198

The first column shows that, on average, a one standard deviation increase in the stated likelihood of losing one's job increases the actual likelihood of job loss in the US by around 4.9 percentage points. Similarly, the coefficients range from 1.5 percentage points for Switzerland to 8 percentage points for Germany indicating a strong correlation between individual's perceived probability of job loss and subsequent outcomes.

Furthermore, the panel structure of the GSOEP, LISS, and SHP allows me to elicit how within-person changes in subjective unemployment beliefs affect actual outcomes. Hence, in columns 3, 5, and 7 I include person fixed effects. On average, a one standard deviation increase in perceived unemployment beliefs increases the probability of losing one's job within the next year by 6.1 percentage points in Germany, 1.5 percentage points in Switzerland, and 3.3 percentage points in the Netherlands. All of the coefficients are highly significant at the 1 percent level. The economic magnitude of these coefficients is considerable. For example, in the Netherlands an individual experiences a job loss within the next year with an unconditional probability of 2.6 percent. If she states a one standard deviation higher subjective unemployment beliefs, it more than doubles the probability of actually losing her job. I find similar effect sizes for the other countries.

Hence, the third fact that emerges from the data is that subjective unemployment beliefs are highly predictive of actual outcomes. This result indicates that even though the level of unemployment beliefs is on average distorted, individuals are able to predict actual outcomes. This further demonstrates that the elicited unemployment beliefs capture useful information for researchers about participants' beliefs.

2.5 Unemployment Beliefs and Risky Share

Finally, I tackle the question whether these unemployment beliefs actually translate into changes in financial decision-making. I argue in this paper that unemployment beliefs represent an extreme form of subjective labor income risk. An increase in perceived labor income risk reduces the individual's incentive to take on other forms of risk like stock investment. Hence, an increase in unemployment beliefs should according to the classic life-cycle model translate into a reduction in the risky share an individual holds.

Testing this hypothesis requires information about both unemployment beliefs as well as asset holdings. Unfortunately, this requirement limits the following analyses to the LISS panel as it is the only one that elicits detailed asset holdings. Starting in 2008, the survey collects every 2 years comprehensive information on a household's assets. I define the risky share as a household's investments over the sum of its net assets. The investments include growth funds, share funds, bonds, stocks, and options. It is not possible to separate the bonds from the other risky assets as all of the above are bunched into one category. However, bonds make only up 3% of Dutch portfolios and should therefore only have a marginal impact on the results. The net assets are calculated as the difference of all assets and all debt. The conditional risky share is then defined as the risky share conditional on holding any risky assets at all and the participation variable is an indicator variable equal to one if a household holds any risky asset.

Table III.6 shows the results of regressing the risky share, conditional risky share, and the participation rate on unemployment beliefs while controlling for actual unemployment. In the first two columns, I regress the risky share on standardized subjective unemployment beliefs both with and without person fixed effects. On average, a one standard deviation increase in perceived job loss risk decreases the risky share by 0.8

Table III.6: This table shows the results of regressing the risky share, conditional risky share, or an indicator variable equal to one if and individual participates in the stock market on standardized subjective unemployment beliefs as well as an indicator variable if an individual is unemployed. Unemployment beliefs are lagged by one year. All regressions include year fixed effects. Additionally, columns 2, 4, and 6 include person fixed effects. Standard errors are clustered by person level, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Risky Share	Risky Share	Cond. Share	Cond. Share	Participation	Participation
Unemployment	-0.008**	-0.010**	-0.030***	-0.022*	-0.006	-0.004
Beliefs(t-1)	(-2.26)	(-2.52)	(-2.74)	(-1.94)	(-0.88)	(-0.54)
Actual	0.011	0.009	0.126*	0.104	-0.021	0.003
Unemployment	(0.55)	(0.39)	(1.90)	(1.43)	(-0.52)	(0.09)
Year FE	YES	YES	YES	YES	YES	YES
Person FE	NO	YES	NO	YES	NO	YES
Observations	4,226	3,152	919	623	4,226	3,152
Adjusted R^2	0.002	0.602	0.004	0.654	0.001	0.689

percentage points without person fixed effects and 1 percentage point in a regression including person fixed effects. These coefficients are statistically significant at the 5 percent level. This change of 1 percentage point is sizable considering the average risky share in the sample is only 8.3 percent.

Similarly, a one standard deviation increase in perceived unemployment beliefs reduces the conditional risky share by 3 percentage points without person fixed effects and by 2.2 percentage points after including fixed effects. This effect is statistically significant at the 1 and 10 percent level, respectively. Again, the economic significance is relatively large given the average conditional risky share of around 25 percent. Finally, in columns 5 and 6 I regress a indicator variable equal to one if a household holds strictly positive share in the risky asset on perceived unemployment beliefs. There is no statistically significant effect observable that participants with higher perceived job uncertainty are less likely to invest or even exit the stock market. However, this is consistent with the theoretical model as I show in the later part of this paper. Distorted unemployment beliefs do not prevent individuals from investing into the stock market as only a fixed participation cost or entry cost can achieve this.

In conclusion, elicited unemployment beliefs are not only predictive of unemployment outcomes but also translate into individual's financial decision making. The findings show that the economic magnitude of the impact of unemployment beliefs on stock market investment is sizable. The effect size is especially surprising given that there actual employment situation does not necessarily change. These results further suggest that perceived unemployment risk can help to understand from a theoretical point of view why households are reluctant to invest in the stock market. Furthermore, it becomes clear that unemployment beliefs elicited in surveys reflect actual beliefs that are important for an individual's financial decision making.

2.6 Discussion of Empirical Patterns

The previous analyses explore various dimensions of elicited unemployment beliefs. The micro data on unemployment beliefs reveals three robust patterns which I summarize in this section. First, individuals persistently overestimate the likelihood of losing their job in the future. The pattern persists across time, countries, and demographics. Cross-sectional sample splits reveal that demographics with on average higher objective likelihood to lose their job also report higher job loss probabilities. This suggests that, on average, individuals are aware of the job loss likelihood they face relative to other demographics. Second, unemployment beliefs are persistent over time. This is the case both on the aggregate level and within individual. The aggregate level findings show that the large distortion of beliefs is not an outlier. The individual level persistence of unemployment beliefs signifies that survey participants do not randomly answer these questions from year to year but their answers correspond to a perceived level of background risk. If in one year this risk increases, they quickly revert back to the low levels. Third, stated unemployment beliefs are highly predictive of future actual unemployment both at the extensive and intensive margin. This result indicates that participants convey private information about future employment outcomes through these probabilities.

Furthermore, I find that changes in subjective unemployment beliefs lead to changes in financial decision making. Unemployment represents an increase in labor income risk which leads households to reduce their exposure to other sources of risk. In line with the classic portfolio model, an increase in unemployment beliefs, therefore, decreases risky asset holding. Overall, these findings suggest that unemployment beliefs stated in surveys do not only reflect noise but rather contain valuable information for researchers about the perceived extreme labor income risk of individuals. Moreover, participants actually consider these information in their financial decision making.

Hence, in the next sections, I incorporate subjective unemployment beliefs in a life-cycle model of consumption and saving where agents decide between saving in risky and risk-free asset. First, I set up a model and calibrate it to the empirical data. Second, I structurally estimate the unobserved model parameters like risk aversion, discount factor, and participation cost. I demonstrate how integrating subjective beliefs helps to fit the model to the data while requiring a lot more reasonable values for the above mentioned parameters compared to the model without distorted beliefs.

3 Model

3.1 Model Specification

I adapt the workhorse model of Cocco et al. (2005) for my purposes. A representative agent with CRRA preferences optimizes her expected lifetime utility by deciding each period how much to consume and how much to invest in the risk-free and risky asset. I denote t as adult age where the individual lives for a maximum of T periods. Agent i's preferences are denoted by:

$$E\sum_{t=1}^{T}\delta^{t-1}(\prod_{j=0}^{t-1}p_j)\{\frac{C_{it}^{1-\gamma}}{1-\gamma}\}$$

where C_{it} is the consumption of individual i at time t, $\delta < 1$ is the discount factor, and γ is the coefficient of relative risk aversion. p represents the survival probability from one period to the next, where p_T is equal to zero. Bequest motives are not considered. Thus, the agent consumes all of her wealth in the final period.

Labor income process. Labor income is given exogenously by:

$$log(Y_{it}) = f_{it} + \nu_{it} + \epsilon_{it}$$

where f_t is a deterministic component dependant on the agent's age and initial income, ν_{it} represents persistent income shocks, and ϵ_{it} idiosyncratic, temporary shocks to income. The persistent income shocks are modeled as:

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

where ζ_{it} is distributed $N(0, \sigma^2_\zeta)$ and uncorrelated with ϵ_{it}. Likewise, ϵ_{it} is distributed $N(0, \sigma^2_\epsilon)$. The deterministic component f_{it} takes the form:

$$f_{it} = \overline{f_t} + \eta_i$$

where $\overline{f_t}$ represents a function of the life-cycle trajectory of income common to all workers. Conversely, η_i is individual specific and assumed to be normally distributed with standard deviation σ_η. Hence, η_i represents the initial dispersion in incomes of workers. On top of that, I apply a flat 15% income tax to labor income.

As soon as an agent hits retirement, income is assumed to be deterministic as a fixed percentage of an agent's last labor income. Hence:

$$log(Y_{it}) = \begin{cases} log(Y_{it}) & \text{if } t < t_R \\ log(Y_{it_R - 1})\lambda & \text{if } t \geq t_R \end{cases}$$

Income in the case of unemployment is modelled as a fixed percentage of an individual's regular labor income:

$$log(Y_{it}) = \begin{cases} log(Y_{it})\kappa & \text{with probability } \omega_t \\ log(Y_{it}) & \text{with probability } (1 - \omega_t) \end{cases}$$

Agents enter unemployment with probability ω_t and consequently receive a transitory income shock of κ. As this is only a transitory income shock, this has no long-lasting impact on a household's labor income trajectory.

The main difference of this model compared to the existing literature is that agents hold subjective beliefs about the likelihood of losing their job. Hence, agents hold the following beliefs about next period's labor income:

$$E_t^{subj}[log(Y_{it+1})] = \begin{cases} log(Y_{it+1})\kappa & \text{with probability } \omega_{t+1}^{subj.} \\ log(Y_{it+1}) & \text{with probability } (1-\omega_{t+1}^{subj.}) \end{cases}$$

Yet, even though individuals hold these distorted beliefs they face the objective probability of losing their job. That means that agents on average severely overestimate the likelihood of losing their job as the data shows that $\omega_t^{subj.} >> \omega_t$.

Stock Market Returns. Each period the agent chooses how much of her wealth after consumption is allocated to the risky asset (henceforth stocks). All remaining wealth is invested into a risk-free asset. Stock returns R_{t+1} are assumed to be log normally distributed with mean μ_s and standard deviation σ_s, whereas the risk-free asset provides a deterministic return of R_f. Furthermore, in line with the literature (e.g. Cocco et al., 2005; Catherine, 2022) I assume that agents face a variable management fee for the stock portfolio. Furthermore, following the literature (e.g. Fagereng et al., 2017) introduce infrequent stock market crashes. Hence, stock returns are given by:

$$R_{t+1} = \begin{cases} \underline{R}_{t+1} & \text{with probability } p_s \\ R_{t+1} & \text{with probability (1-}p_s\text{)} \end{cases}$$

where $\underline{R}_{t+1}$ represents the return of the risky asset in case of a stock market crash. This event occurs with probability p_s.

Participation Cost. If an agent chooses to invest in the risky asset, she incurs a fixed per-period participation cost Φ. Introducing a participation cost is crucial for non-participation. In the absence of participation cost it is always optimal for an agent to invest a non-zero amount into the risky asset (Merton, 1969). Intuitively, this penalty represents both the actual cost of setting up a broker as well as the psychological and physical cost of doing research on the stock market.

3.2 Investor's Optimization Problem

The investor's optimization problem is solved by dynamic programming. The model setup results in the following Bellman equation:

$$V_{it}(X_{it}) = \max_{C_{it}\geq 0, 0\leq \alpha_{it}\leq 1} [U(C_{it}) + \delta p_t E_t V_{i,t+1}(X_{i,t+1})] \;\; for\ t < T,$$

where

$$X_{i,t+1} = Y_{i,t+1} + (X_{it} - C_{it})(\alpha_{it} R_{t+1} + (1-\alpha_{it})R_f) - \mathbb{1}^{\alpha_{it}>0}\Phi$$

The model is solved by backward induction where the terminal value of this optimization problem is derived from the fact that the agent consumes all of his remaining wealth in the final period. Intuitively, the agent trades off each period utility from consumption versus utility from deferred consumption. Hence, first she chooses her optimal level of consumption. Second, she decides how much to allocate to the risky and the risk-free asset, respectively. For more details regarding the implementation of the solution please refer to appendix B.

4 Data and Calibration

4.1 Model Moments

The goal of the structural estimation is to match the empirically observed evolution of wealth and investment in the risky asset over a household's life-cycle. Hence, I first compute household's portfolios utilizing the Survey of Consumer Financials (SCF). The survey is administered every three years and surveys around 6500 US households as of the most recent wave.

Household Portfolios. I compute the risky share based on the eleven waves of the SCF between 1989 and 2019. Following Catherine (2022), I exclude business owners and household whose net worth is less than 0. On top of that, I exclude individuals that are not part of the labor force (*lf*=0). Consistent with the model, I define households' wealth as *networth* divided by the average labor income in the given year for households that are between 23 and 65 years and part of the labor force. The risky share is defined as *equity* divided by a household's *networth* for households with a *networth* of at least $1000. The SCF equity variable includes both direct and indirect holdings in mutual funds and retirement accounts.

Household Wealth. Initial wealth at the birth of each agent is assumed to be normally distributed among households. Mean and standard deviation of that distribution are estimated from the *networth* of 23 and 24 year old's in the SCF. Simulated agent's initial wealth is then drawn from that distribution.

Table III.7: This table shows summary statistics for the Survey of Consumer Financials (SCF) dataset spanning the years 1989 to 2019. Only individuals between the ages of 23 and 81 are included. Labor income is calculated for individuals between the ages of 23 and 65.

	Mean	Std. Deviation	Observations
Age	43.36	12.55	136,285
Wealth	285,847.79	1,145,659.09	136,285
Labor income	77,280.89	134,534.22	136,285
Stock market participation	0.49		136,285
Equity share	0.17	0.46	116,599
Cond. equity share	0.30	0.58	70,677

4.2 Household Income Process

The household income process is given by the parameters $\overline{f_t}$, σ_ζ, σ_ϵ, σ_η, λ, and κ. I use the Panel Study of Income Dynamics (PSID) to estimate all of the above mentioned parameters.

Labor Income. I estimate the deterministic component of labor income as well as the standard deviation of the permanent and transitory labor income shocks using the PSID. I closely follow the procedure of Carroll and Samwick (1997) and Cocco et al. (2005) and fit $\overline{f_t}$ using a third-order polynomial to the PSID data for households whose head is between 23 and 65 while controlling for household characteristics like marital status, household composition, and education. Based on the deterministic labor income profile, I estimate the error structure of the labor income process using the variance decomposition as described by Carroll and Samwick (1997). For more details, please refer to appendix A2. Furthermore, I find σ_ζ to equal 0.117 and σ_ϵ to equal 0.290. My estimates for $\overline{f_t}$, σ_ζ, and σ_ϵ are similar to the ones estimated by Cocco et al. (2005) or Catherine (2022).

Finally, initial income is also assumed to be log-normal distributed with a standard deviation σ_η. I derive the standard deviation of initial income from the distribution of wages of 22 and 23 year olds in the PSID data and find a value of 0.139 for σ_η.

Retirement Income. The replacement rate in retirement λ is approximated as a fixed percentage of an agent's income before retirement using the PSID data. Following Fagereng et al. (2017), I calculate the replacement ratio as mean income 5 years after retirement divided by mean income 5 years before retirement. I find that, on average, households earn 67.1 percent of their pre-retirement income after reaching retirement. This estimate is again close to the estimate of Cocco et al. (2005).

Unemployment Benefits. I estimate unemployment income replacement rate κ by dividing a household's unemployment income by last year's labor income if the head of the household was unemployed for at least 3 months in the year and regularly employed in the previous year. I find a unemployment income replacement ratio of 0.065 which appears low. However, there is considerable uncertainty surrounding the average replacement ratio in the US (c.f. appendix A3) and some estimates by Martin (1996) indicate also very low values.

Furthermore, the actual probability ω_t of losing one's job within one year are taken from S. Choi, Janiak, and Villena-Roldán (2015). As they provide unemployment probabilities for males and females separately, I weight these probabilities by labor force participation rate to calculate the unemployment probabilities for the overall population.

Unemployment beliefs. I utilize the question *"What do you think is the percent chance that you will lose your job during the next 12 months?"* from the Survey of Consumer Expectations (SCE) to calculate subjective unemployment beliefs. I estimate the subjective unemployment beliefs at each age by fitting a fourth degree polynomial through the mean of the reported percent chance of loosing her job within the next 12 months. I chose this approach due to the short time period covered by the SCE even though it does not allow me to explicitly disentangle cohort from age effects.

4.3 Preset Parameters

Agent. Households start working at the age of 23 and live to a maximum age of 100 when they die with probability one. At the age of 65, households stop working and retire. Survival probabilities are taken from from Social Security actuarial life tables.

Stock Market. The returns of the risky asset are assumed to be normally distributed with $R_{t+1} \sim N(\mu_s, \sigma_s)$. I set the mean of the return equal to 0.082 minus the variable management fee of 0.015 and the standard deviation equal to 0.159 which is the historical mean and volatility of the S&P500 since 1927. I set the probability of a stock market crash p_s to 2 percent which results in a return of the risky asset of -40 percent as estimated by Barro (2009). Furthermore, as usual in the literature I set the risk-free rate at 2 percent.

Table III.8: This table summarizes the preset and estimated model parameters for the structural estimation. The first column names the parameter, the third column presents the calibrated parameter, and the last column describes the data source.

Parameter		Value	Source
Agent:			
Age of first employment	t_0	23	
Age of retirement	t_R	65	
Maximum age	T	100	
Assets:			
Average return risky asset	μ_s	0.082	S&P500 historical returns
Standard deviation risky asset	σ_s	0.159	S&P500 historical returns
Probability of stock market crash	p_s	0.02	Barro (2009)
Proportional management fee		0.015	Catherine (2022)
Return on risk-free asset	R_f	1.02	Catherine (2022)
Income Process:			
Effect of *age* on log wage	f_1	0.115	PSID
Effect of $age^2/10$ on log wage	f_2	-0.020	PSID
Effect og $age^3/100$ on log wage	f_3	0.001	PSID
Constant	f_0	-1.620	PSID
Std. of transitory income shocks	σ_ϵ	0.290	PSID
Std. of permanent income shocks	σ_ζ	0.117	PSID
Std. of initial income distribution	σ_η	0.139	PSID
Unemployment probability	ω_t		S. Choi et al. (2015)
Unemployment income	κ	0.065	PSID
Replacement ratio	λ	0.671	PSID

5 Structural Estimation

The aim of the structural estimation is to elicit the combination of the unobserved parameters risk aversion (γ), discount factor (δ), and participation cost (Φ) that fits the model best to the empirical moments. Thus, I can compare which level of these parameters is required in the models with and without distorted beliefs. I target are the evolution of the unconditional and conditional risky share, participation rates, and wealth over the agent's life-time until retirement to estimate these unobserved parameters. Specifically, each moment represents the average of the aforementioned variables over three consecutive years. Hence, I compute the averages of these values in the age interval from [23;25] to [62;64].

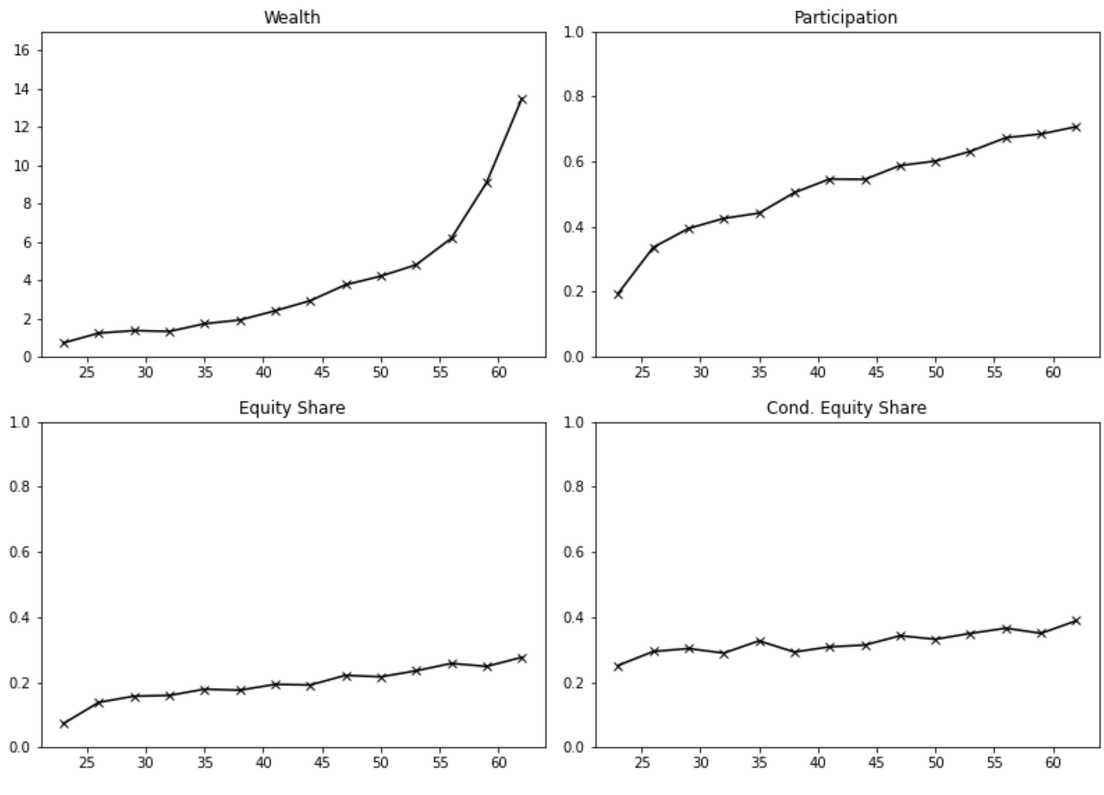

Figure III.2: This figure shows the empirical moments estimated from the Survey of Consumer Finances (SCF). The upper left panel plots the evolution of wealth across 3-year age cohorts net of cohort and year effects. Equivalently, the upper right panel displays the participation rate, the lower left panel shows unconditional share, whereas the lower right panel plots the conditional risky share.

I estimate the empirical moments from the SCF data by averaging risky share, conditional risky share, stock market participation rates, and wealth for the 14 three-year age groups. Following Deaton and Paxson (1994), I disentangle age effects from time and cohort effects by regressing each variable of interest on a set of age, year, and cohort dummies. The multicollinearity is addressed by assuming that the year dummies sum to zero and are orthogonal to a time trend. Figure III.2 shows each of the empirical moments over the life-cycle. Similar to Catherine (2022), I find that risky share, participation rates, and wealth increase until retirement. Given this procedure, I have 14 times 4 moments equal to 56 moments. The simulated method of moments aims to minimize the following equation:

$$(\mathbf{m} - \hat{\mathbf{m}}(\gamma, \delta, \Phi))'\mathbf{W}(\mathbf{m} - \hat{\mathbf{m}}(\gamma, \delta, \Phi))$$

where $\mathbf{m}$ are the moments estimated from the SCF data and $\hat{\mathbf{m}}(\gamma, \delta, \Phi)$ are the predicted moments from the model given risk aversion, discount factor, and participation cost. $\mathbf{W}$ represents a weighting matrix, which is the inverse of the bootstrapped covariance matrix of the moments calculated from the SCF (c.f. appendix C1). Depending on the specification, not all moments are targeted simultaneously. Intuitively, the discount factor (δ) determines the wealth accumulation, risk aversion (γ) how much is allocated to the risky asset, and the participation cost (Φ) deters households with low wealth levels to participate in the stock market.

6 Estimation Results

6.1 Model without Participation Cost

In this section, I describe the results of the SMM procedure for the model without participation cost. I begin by estimating the coefficient of relative risk aversion (γ) and the discount factor (δ). Columns 1 and 3 of Table III.9 display the estimated parameters for the baseline model with objective unemployment beliefs and the model with distorted beliefs, respectively. Panel B reports the associated targeted life-cycle moments. When estimating the model without participation cost, I only target the evolution of wealth over time as well as the risky share. It is futile to target the stock market participation rate as not including participation cost means that agents always hold a strictly positive part of their wealth in the risky asset (Merton, 1969). Thus, the conditional risky share equals the unconditional risky share.

Table III.9: This table shows the results of the structural estimation. Panel A displays the coefficients estimated by the SMM and Panel B shows the targeted life-cycle moments. In columns 1 and 2 agents hold objective unemployment beliefs, whereas in columns 3 and 4 they hold distorted beliefs. Additionally, columns 2 and 4 assume a fixed per period participation cost.

	Baseline		Distorted Beliefs	
	(1)	(2)	(3)	(4)
Panel A: Estimated Parameters				
Relative risk aversion	18.056	12.739	11.846	7.792
Discount factor	0.455	0.623	0.749	0.719
Fixed participation cost		0.0166		0.0147
Panel B: Targeted Life-cycle Moments				
Risky share	✓		✓	
Conditional risky share		✓		✓
Participation rate		✓		✓
Wealth	✓	✓	✓	✓

With objective unemployment probabilities, the agents require a relative risk aversion of 18.056 and a discount rate of 0.455 to match the evolution of wealth and the risky share. Clearly, these parameter values are highly implausible given what the experimental economics literature considers a reasonable range for risk aversion and the discount factor. Conversely, including distorted unemployment beliefs improves the estimated parameters considerably. The optimal parameters of risk aversion drops to 11.846, whereas the discount factor increases to 0.749. Both parameters substantially move towards more likely estimates. This improvement in estimated model parameters is astonishing given that there are no material changes for the agent as they still face the objective probability of losing their job and thereby still have a relatively low probability of experiencing this disaster shock to their labor income.

Panel A of figure III.3 plots the empirical moments estimated from the SCF data as well as the moments estimated in the structural estimation both for the baseline model as well as the model with distorted unemployment beliefs. This figure demonstrates that the SMM procedure manages to match the targeted wealth and risky share moments successfully. Obviously, the estimation does not match the not targeted moments as without participation cost every agent participates in the stock market.

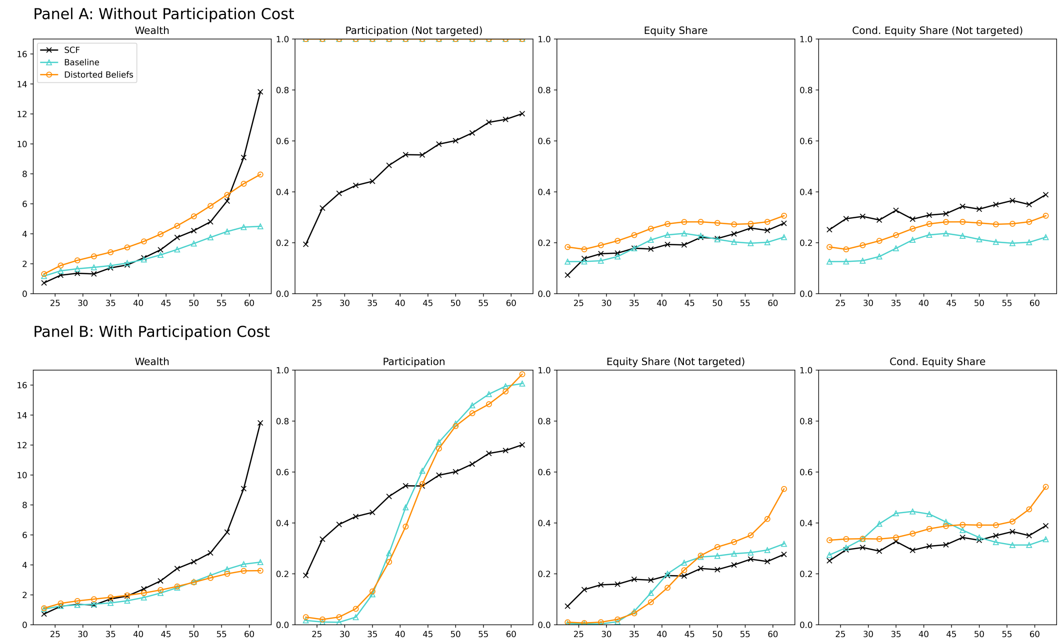

Figure III.3: This figure shows the empirical moments (black) that are targeted by the structural estimation over the life-cycle as well as the estimated moments of the baseline model (green) and the model with distorted unemployment beliefs (orange). Panel A displays the moments for the model without participation cost and panel B exhibits the moments for the model with participation cost. In panel A, I target wealth and risky share, whereas in panel B I target wealth, participation rate, and conditional risky share.

Overall, the estimated parameters are even for the model with distorted beliefs highly unlikely. This is not surprising as the model does not consider housing. Housing represents the largest asset for most households which is associated with either rent or interest payments. The lack of this model component encourages wealth accumulation. Hence, matching the observed wealth moments requires low values of the discount factor δ to encourage consumption and prevent excessive wealth accumulation. Thus, the focus should be the comparison of estimated parameters between the model with and without distorted beliefs. Here, we see that the relative risk aversion drops by one third and the discount factor almost doubles when considering elicited beliefs in the classic life-cycle model.

6.2 Model with Participation Cost

Next, I include a fixed per period participation cost in the model. Again, I estimate the relative risk aversion (γ) and the discount factor (δ) as well as the participation cost (Φ). In this specification of the SMM procedure I target the wealth, conditional risky share, and participation rate over the life-cycle. I do not target the unconditional risky share as it is jointly determined by the conditional risky share and participation rate. Columns 2 and 4 of Table III.9 show the results of the estimation.

In the baseline model without distorted beliefs, agents require a risk aversion parameter of 12.739 and a discount rate of 0.623 as well as a participation cost of 1.7 percent to match the empirical moments. Compared to the baseline model without participation cost, this represents a significant improvement. Nevertheless, comparing column 2 and 3 reveals that the model with distorted beliefs but without participation cost matches the empirical moments for a more reasonable level of discount factor and risk aversion. In the model with distorted unemployment beliefs, the risk aversion parameter for the optimal results further drops to 7.792. At the same time, the required discount factor increases to 0.719 and the participation cost decreases to 1.5 percent. Once more, including distorted unemployment beliefs reduces the required risk aversion considerably while a lower fixed participation cost is required. Similarly, the discount factor increases.

Panel B of Figure III.3 indicates a reasonable fit of both models. The models tightly fit the empirical conditional equity share. At the same time, the empirical wealth accumulation is closely matched for younger individuals, but does not match the large increase in wealth before retirement. The one factor that is difficult to match is the participation rate as it exhibits a moderate increase in the data which the theoretical model does not allow for. Nonetheless, most papers structurally estimating life-cycle models face this issue (e.g. Fagereng et al., 2017; Catherine, 2022). Catherine (2022) proposes that heterogeneous participation cost would solve this problem. However, this is beyond the scope of this paper.

In conclusion, these findings demonstrate that including elicited unemployment beliefs into the standard model can significantly contribute to matching unobserved model parameters like risk aversion and discount factor to the values observed in the experimental economics literature. In the next section, I further explore the mechanisms behind these improvements. For that purpose, I investigate the agent's policy functions regarding investments in the risky share when she holds distorted beliefs compared to when she holds objective beliefs.

7 Discussion

7.1 Empirical versus Model Policy Function

In general, life-cycle models of consumption and saving predict that the optimal risky share declines in the wealth-to-earnings ratio while controlling for age. Intuitively, labor income has bond like properties. Hence, a higher share of labor income in your future wealth realizations increases the incentive to invest into the risky asset. However, we observe empirically that the relationship between wealth-to-earnings ratio and the risky share is flat. To demonstrate this conflict, I regress the conditional risky share on a set of wealth-to-earnings decile indicator variables as well as age dummies. Figure III.4 plots the resulting coefficients of the wealth-to-earnings deciles for the SCF data and the models estimated in columns 2 and 4 in table III.9.

Clearly, the empirically observed conditional risky share is flat in the wealth-to-earnings ratio. Conversely, the risky share is monotonically downward sloping in the wealth-to-earnings ratio in the baseline model without distorted beliefs as predicted by economic theory. Accounting for distorted unemployment beliefs appears to resolve this puzzle. The relationship between wealth-to-earnings and the risky share is completely flat in the deciles 3 to 8 in the model with distorted unemployment beliefs. Intuitively, the distortion in unemployment beliefs increases the perceived riskiness of future labor income which makes labor income more stock like. This induces agents to reduce the riskiness of their future wealth realizations. Interestingly, this effect is stronger at lower wealth-to-earnings ratios as labor income constitutes a larger part of future total income which explains why the largest reduction in conditional risky share is observable for wealth-to-earnings deciles 3 and 4.

Nevertheless, the lowest two wealth-to-earnings deciles are not affected by distorted unemployment beliefs as the conditional risky share is always equal to 100 percent for these households. Yet, this issue is addressed in the model by the fixed participation cost which prevents these hand-to-mouth households from investing in the stock market. Finally, the relationship between wealth-to-earnings and the conditional risky share only becomes downward sloping in the highest two deciles. This is not surprising as these represent households that have such a high level of wealth that a labor income shock barely affects their consumption. Overall, these results demonstrate that distorted unemploy-

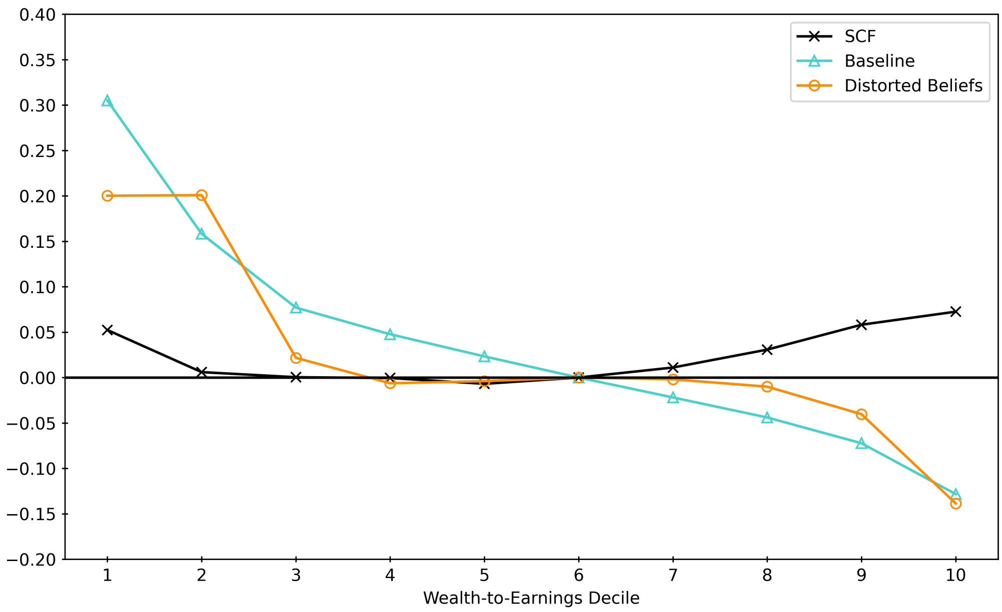

Figure III.4: This figure shows the empirical policy function and the policy functions suggested by the models. I regress the conditional risky share on a set of wealth-to-earnings decile indicators and age dummies in the SCF data (black), the baseline model (green), and the model with distorted beliefs (orange). I also include year fixed effects in the SCF specification. The models are calibrated to the estimates of column 2 and 4 in table III.9.

ment beliefs flatten out the relationship between wealth-to-earnings and conditional risky share for a majority of the population. Hence, by matching the empirical policy functions in the model more closely, the model can fit the empirical moments with more realistic levels of risk aversion.

7.2 Policy Functions and Age

In this part, I further explore how distorted unemployment beliefs affect an agent's policy functions and subsequently aggregate outcomes for agents at different ages. Hence, figure III.5 plots an agent's policy functions depending on her wealth-to-earnings ratio. The models are parameterized according to the estimates of columns 2 and 4 in table III.9. In the upper panel, I present the optimal conditional risky share for the agent with objective beliefs (left) and the agent with distorted beliefs (right) at the ages 25, 40, and 55.

At wealth levels close to zero, agents optimally chooses to invest 100 percent into the risky asset. Intuitively, if human capital is a lot larger than wealth, stock market risk is inconsequential for the agent's consumption. Yet, in the model the fixed participation cost prevents these households from investing into the risky asset. Moving towards a higher wealth-to-earnings ratio leads to a sharp drop in the optimal conditional risky share both for the model with and without distorted unemployment beliefs. This reduction in the risky share is induced by the presence of unemployment risk in both models. However, the optimal risky share increases again in the baseline model at a wealth-to-earnings ratio of 1, whereas it remains flat in the model which includes distorted beliefs. Subsequently, the optimal risky share decreases monotonically.

Hence, distorted unemployment beliefs flatten the policy function for wealth-to-earnings ratios of less than 4. These are the levels of wealth of around 75 percent of the population in the SCF. Thereby, the model with distorted unemployment beliefs can match the risky share over the life-cycle with significantly lower levels of risk aversion than the conventional model. Interestingly, the low probability of actual unemployment is sufficient to prevent individuals at a young age and an intermediate level of wealth to invest larger amounts into the risky asset which illustrates the importance of considering disaster labor income shocks in these models.

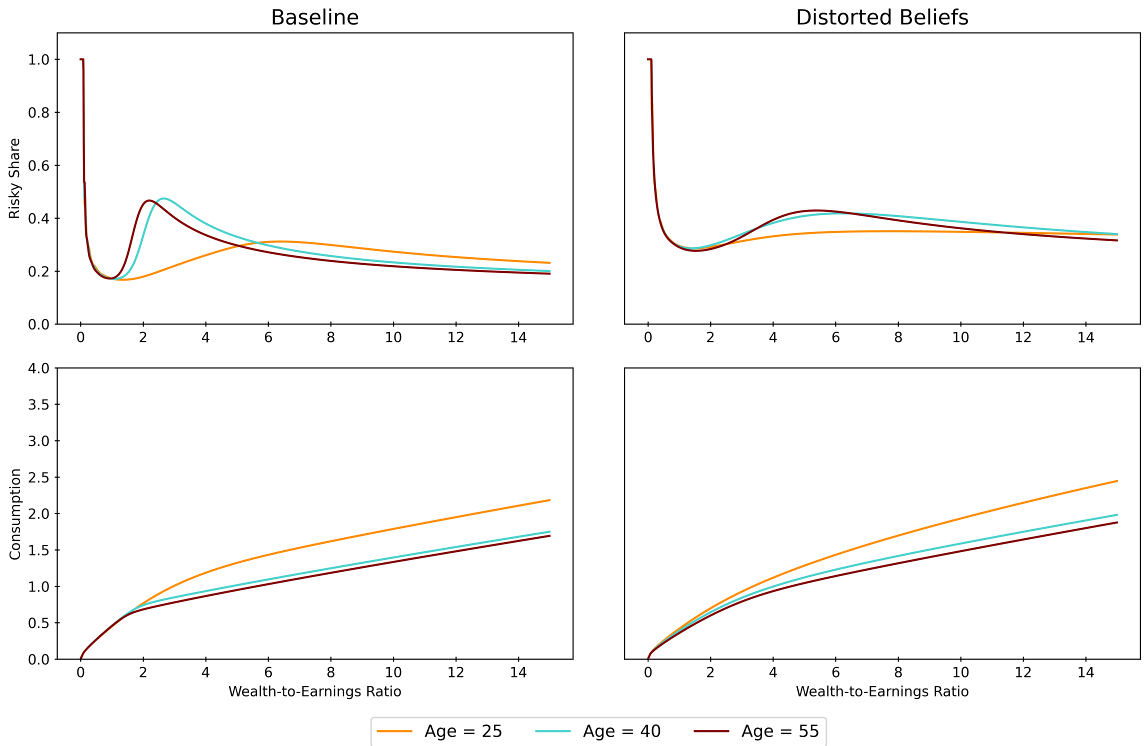

Figure III.5: This figure shows the agent's optimal conditional risky share and consumption depending on her wealth-to-earnings ratio for various ages. The first column displays the policy functions for an agent that holds objective beliefs, whereas the second column presents them for an agent with distorted beliefs. The upper panel plots the risky share depending on the agent's wealth for the ages 25 (orange), 40 (blue), and 55 (red). Similarly, the lower panel graphs the consumption function. The models are calibrated to the estimates of column 2 and 4 in table III.9.

Finally, the lower panel of Figure III.5 reveals that the consumption function of the agents is steeper in the model with distorted beliefs compared to the model without distorted beliefs. This effect is especially pronounced for the younger households. This increased consumption at high wealth levels reduces capital accumulation of more wealthy households and thereby matches the empirically wealth increase until retirement. However, at low levels of wealth-to-earnings ratio the consumption function is slightly steeper in the baseline model. Intuitively, agents with little savings or early on in their career prepare themselves for this disaster income shock by increasing their precautionary savings and thereby reducing their consumption.

Overall, these graphs shed further light on the mechanisms that improve the model fit when incorporating distorted beliefs. Inflated unemployment beliefs increase the agent's perceived labor risk. This reduces the incentive to invest in the risky asset at a given level of wealth significantly. This effect is especially pronounced at wealth-to-earnings ratios of 1 to 4. Comparing this with the model moments (c.f. Figure III.3) reveals that, on average, this is the case at the ages 30 to 50 and thereby affects a large part of the population of the agents. Hence, the model with distorted unemployment beliefs requires less risk averse agents to prevent stock market investment.

7.3 Policy Functions and Unemployment Probability

Next, I explore how varying levels of perceived unemployment probabilities affect the decision to invest in the risky asset depending on an agent's age. Figure III.6 displays the policy function for investing into the risky share at the ages of 25, 35, 45, and 55 for various perceived unemployment probabilities. If there is a zero probability of an agent facing a labor income disaster shock like unemployment, all four graphs exhibit the typical policy function pattern established by Cocco et al. (2005). At relatively low levels of wealth, the agent should optimally invest all of his cash-on-hand into the risky asset. After reaching a high wealth-to-earnings ratio, this share monotonically decreases.

As expected, introducing disaster labor income risk significantly reduces the share that is optimally invested into the risky asset. Again, this reduction is especially pronounced at intermediate wealth-to-earnings ratios and at 35 to 55. Interestingly, the absolute level of the perceived job loss likelihood only matters for older individuals at a narrow window of wealth-to-earnings. It seems to be more important to include a labor income shock at all than the exact likelihood of it occurring. Yet, for the 25 year old individuals, the level of the unemployment probability reduces risky share across the whole range of the wealth distribution. Once more, the spike at extremely low levels of wealth which still persists after introducing unemployment beliefs vanishes after including a fixed per-period participation cost. The risky share drops to zero for these agents. Thus, the overall policy function flattens.

In conclusion, three patterns emerge from the policy functions. First, introducing

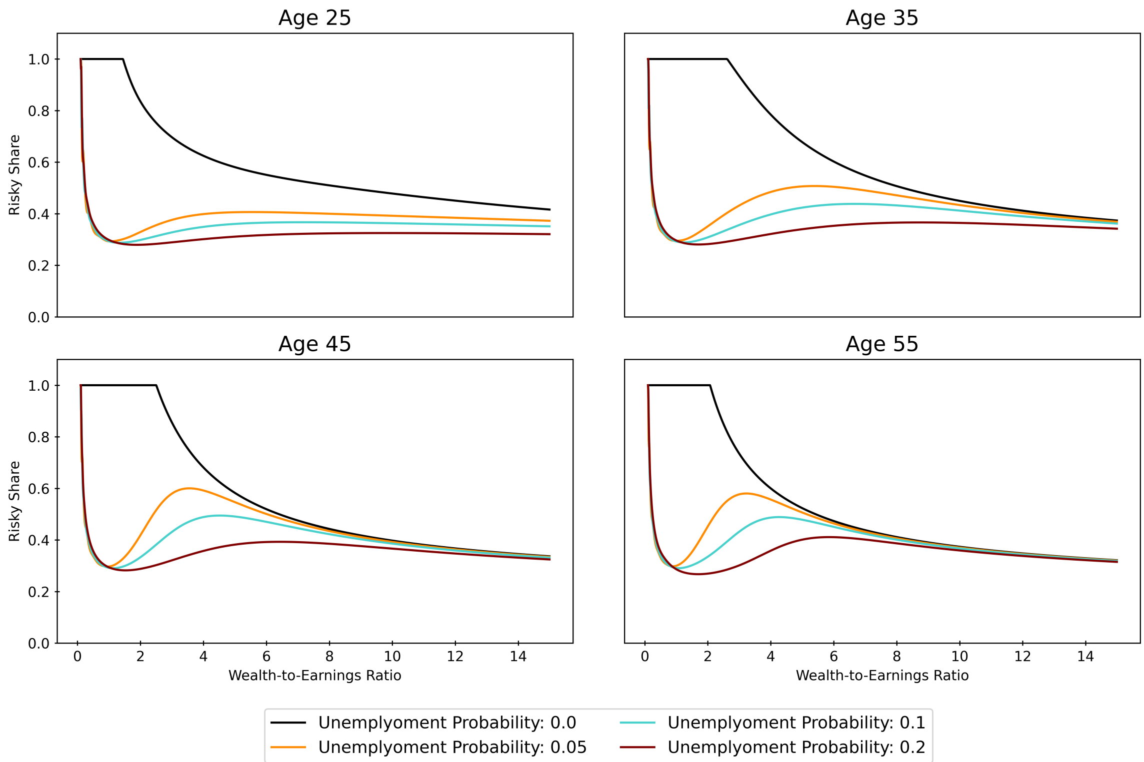

Figure III.6: This figure displays the policy functions of four agents with varying levels of perceived unemployment probabilities for investing into the risky asset depending on the wealth-to-earnings ratio. I plot the agents' policy functions at the ages of 25 (upper left), 35 (upper right), 45 (lower left), and 55 (lower right). The perceived unemployment probability is either 0 percent (black), 5 percent (orange), 10 percent (blue), or 20 percent (red). The models are calibrated to the estimates of column 2 in table III.9.

a perceived tail labor income risk via unemployment beliefs is crucial to induce a risky share policy function that is close to becoming flat in the wealth-to-earnings ratio which is necessary to match the upward sloping risky share by age observed in the SCF data. Second, the level of unemployment beliefs has the largest impact at intermediate levels of wealth. Looking at the average wealth across ages reveals that this level of wealth is exactly matched for individuals between 35 and 55 years. Hence, having a higher perceived job loss likelihood in these years prevents a large increase in risky share before retirement. Third, the level of unemployment beliefs has a persistent negative effect on the optimal risky share across the whole wealth distribution for younger individuals. Hence, introducing distorted beliefs is essential to generate the on average low levels of investment in the risky asset at young ages.

7.4 Effect Decomposition

In this section, I compare the effect of distorted unemployment beliefs and stock market crashes on the equity share over the life-cycle. Hence, I simulate the model (a) without distorted unemployment beliefs and stock market crashes, (b) only with distorted unemployment beliefs, (c) only with stock market crashes, and (d) the full model with stock market crashes and distorted beliefs. I parameterize the model with the estimated optimal parameters of column 3 and 4 of table III.9. Figure III.7 plots in the upper panel the optimal equity share over the life-cycle without participation cost and in the lower panel the optimal equity share for the model including a fixed participation cost. On the right side, I show the net effects i.e. how much including these components of the model reduces the equity share.

Panel A of figure III.7 illustrates the importance of considering distorted beliefs in the model without participation cost. Without distorted beliefs, the optimal risky share exhibits a strongly hump-shaped pattern which peaks at around age 40. Conversely, including distorted beliefs flattens the equity share at these ages. Hence, distorted unemployment beliefs allow to match the flat and slightly increasing equity share over the life-cycle. Furthermore, the figure demonstrates that the results are not driven by stock

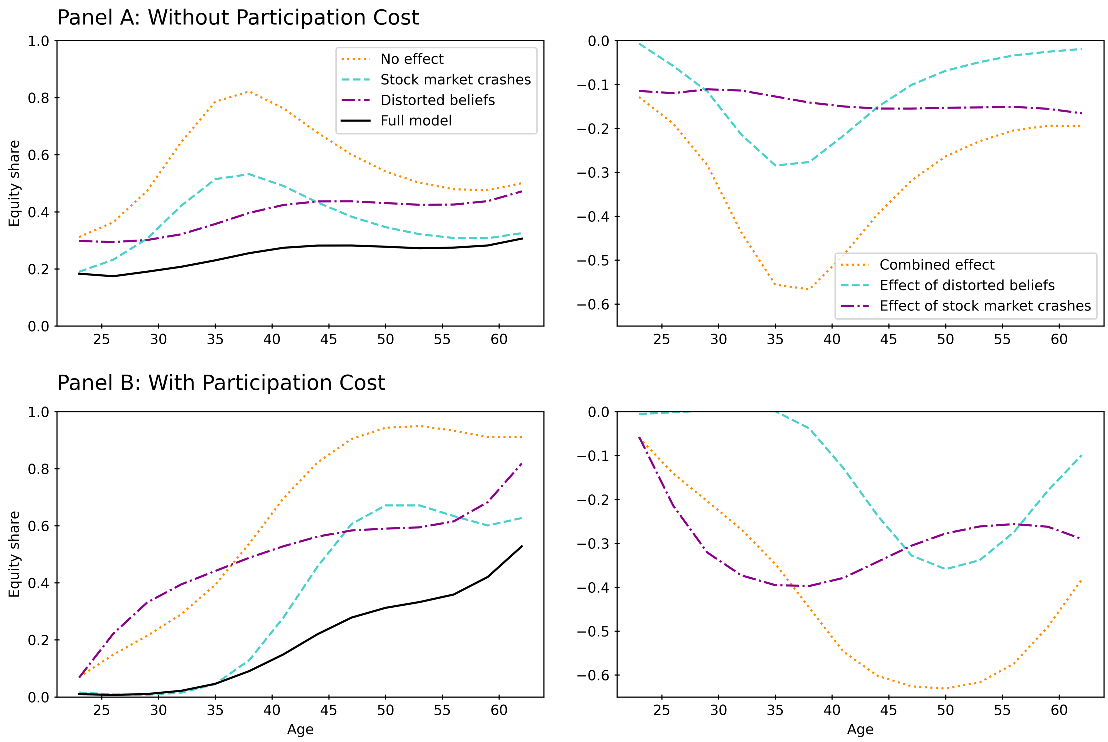

Figure III.7: This figure decomposes the effect of distorted unemployment beliefs and stock market crashes on the optimal equity share over the life-cycle. The upper left panel plots the equity share for the full model without participation cost in black, the model with only distorted beliefs in magenta, the model with only stock market crashes in teal, and the model without stock market crashes and distorted beliefs. The upper right panel plots the change of including distorted beliefs and stock market crashes compared to the full model. The lower panel plots the optimal equity share for the same models but including a fixed per period participation cost as well as the net effects in the lower right panel. The models are parameterized with the optimal estimated parameters from column 3 and 4 of table III.9.

market crashes as the largest reduction in equity share is achieved by the distorted unemployment beliefs.

Similarly, panel B shows that distorted beliefs again flatten the optimal equity share over the life-cycle especially before retirement. Simultaneously, introducing stock market crashes plays a more pronounced role in reducing the optimal equity share for younger households compared to the model without participation cost. The participation cost already prevents young individuals from participating in the stock market and therefore substitutes the increased perceived labor income risk due to distorted beliefs. However, distorted beliefs are crucial in achieving a flat and increasing equity share. In conclusion, distorted unemployment beliefs enable the model to fit a flat and increasing equity share over the life-cycle. This would not be able to achieve by simply introducing stock market disasters.

8 Conclusion

In this paper, I propose that taking beliefs elicited from survey responses seriously can significantly improve the explanatory power of the standard life-cycle model of consumption and saving in two assets. For this purpose, I establish three facts surrounding unemployment beliefs in the first part of the paper. First, survey participants on average severely overestimate the likelihood of losing their job in the future. This discrepancy can be observed for four developed countries over the last 20 years. Second, unemployment beliefs are highly persistent at low reported probabilities. Nevertheless, if an individual reports high levels of unemployment beliefs, they quickly revert back to the low mean. Third, unemployment beliefs are highly predictive of actual outcomes which suggests that they contain private information about an individual's labor income risk. Furthermore, I show in reduced form regressions that within person increases in the perceived job loss likelihood indeed significantly reduce the risky share of individuals. Hence, participants seem to consider unemployment beliefs in their portfolio optimization.

Taking all of these findings into account suggests that elicited unemployment beliefs are not just pure noise but contain valuable information for researchers about individuals' unemployment beliefs. Hence, I augment the classic life-cycle model of consumption and saving in a risky and risk-free asset by the distorted unemployment beliefs. Next, I structurally estimate unobserved model parameters, like risk aversion, discount factor, and participation cost, that optimally fit the the model to the evolution of wealth, risky share, and stock market participation rate observed in the data. I find that including distorted beliefs in the model leads to considerably more reasonable parameter estimates both for risk aversion as well the discount factor compared of the baseline model. Intuitively, larger labor income risk mostly affects individuals with low wealth levels as they need to increase their precautionary savings to ensure that they can maintain their consumption level in the next period if they actually face unemployment. Hence, the policy function for investing in the risky share becomes nearly upward sloping. This is in line with the empirical observation that wealthier households invest more into the stock market.

In conclusion, the results of my paper demonstrate that subjective unemployment beliefs can help to explain low stock market participation rates both at the intensive margin. This finding has implications both for researchers as well as policy makers. On the one hand, my paper provides evidence that considering subjective beliefs in the classic life-cycle model has the potential to greatly increase the model fit. Unemployment beliefs are only a specific, yet important, belief households have to form. Recent research has for example explored how subjective income growth (Rozsypal & Schlafmann, 2023) or subjective mortality beliefs (Heimer et al., 2019) help to improve theoretical models. However, households form a plethora of economic beliefs which could severely alter their economic behavior. Hence, exploring these in surveys could further this strand of the academic literature. On the other hand, from the perspective of a policy maker it could be a sensible decision to provide more generous unemployment benefits if one would want to increase stock market participation rates. Unemployment benefits partially insure households against the large perceived labor income risk they face and thereby increase the incentive to invest in the risky asset. Similarly, stricter labor laws might reduce the level of distortion and thereby increase participation rates.

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A Micro Data

A.1 Unemployment Beliefs and Actual Unemployment

Table 10 shows the wording of the questions of the various surveys employed in this paper. The most important difference across the panels is that the SCE and LISS ask about the likelihood to lose their job on a continuous percentage scale from 0% to 100% whereas GSOEP and SHP elicit unemployment beliefs on a discrete scale from 0 to 10. However, the descriptive statistics in Table III.2 reveal that unemployment beliefs do not differ substantially from each other with the exception of the SHP. The large discrepancy in the SHP seems to stem from the scale employed by the panel. The unemployment belief scale of the SHP associates a 10 (the highest value) with a "real risk" of job loss whereas the other surveys assign absolute certainty to a value of 100%. Hence, it is not surprising that participants in the SHP on average report the highest likelihood of job loss.

Table 10: This table shows the wording of the unemployment beliefs question for the four surveys SCE, GSOEP, LISS, and SHP.

Survey	**Question Wording**
SCE	*What do you think is the percent chance that you will lose your job during the next 12 months?*
GSOEP	*How likely is it that you will experience the following career changes within the next two years? Please estimate the probability of such a change taking place on a scale from 0 to 100, where 0 means such a change will definitely not take place, and 100 means it definitely will take place. Will you lose your job?*
LISS	*Do you think that there is any chance that you might lose your job in the coming 12 months? You can indicate this in terms of a percentage. 0% means that you are sure that you will not lose your job, and 100% means that you are sure that you will lose your job.*
SHP	*How do you evaluate the risk of becoming personally unemployed in the next 12 months, if 0 means "no risk at all" and 10 "a real risk"?*

A.2 Labor Income Process

I largely follow the procedure of Carroll and Samwick (1997) and Cocco et al. (2005) for estimating the labor income process based on the PSID data. Following Cocco et al. (2005), I use a broad definition of labor income and include total reported labor income plus unemployment compensation, workers compensation, social security, supplemental social security, other welfare, child support, and total transfers both for the household head and the spouse. However, I adjust a few details. First, I only include households where the head is working and exclude unemployed individuals as the income of unemployed households is estimated separately. Second, I do not estimate the income process separately for different education groups but rather control for the educational status in the first stage of the regression.

In the first step, I regress the log of total income on household composition, marital status, education, and age dummies. Next, I fit a third-order polynomial through the age dummies to get the deterministic labor income profile $\overline{f}$. In a second step, I estimate the error structure of the income process, namely σ_ϵ and σ_ζ. For that purpose, I utilize the the variance decomposition of Carroll and Samwick (1997). I calculate the change in log income net of the deterministic income component for all possible time horizons. Then, I regress the variance of each of these time horizons on time horizon and a constant term equal to 2. The coefficient of the time horizon variable represents σ_ζ^2 and the coefficient of the constant term is σ_ϵ^2.

A.3 Unemployment Benefits

It is difficult to estimate reliable replacement ratios for unemployment benefits as the legal frameworks differ vastly across US states. First, the cap on unemployment benefits varies from $235 a week in Mississippi to $823 a week in Massachusetts. On top of that, the percentage of pre unemployment wages used to calculate unemployment benefits differs by state. Second, individuals are only eligible for unemployment benefits if they worked for at least four quarters and have been laid off by their employer without good cause. In practice that means that the rates of benefit recipiency are low. In March 2022, the rate averaged at only 29% with the lowest rate of 7.6% in Florida[2]. Third, the maximum time span for which an individual can collect unemployment benefits ranges from 12 weeks in Florida to 26 weeks in the majority of states.

Given the uncertainty surrounding the actual take up of unemployment benefits and a lack of census data, I estimate the unemployment benefit replacement rate using the PSID data. I utilize all PSID family questionnaires from 1970 onward and drop the Survey of Economic Opportunities subsample to obtain a representative sample of the US population. I estimate the replacement rate for unemployment benefits as the head's income from unemployment benefits divided by last wave's labor income if the head was unemployed in this wave and never unemployed in the previous wave. Furthermore, I require individuals to be unemployed for at least 12 weeks.

B Model Resolution

The model is solved by backward induction. The last period's solution 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 a policy function that derives an agent's optimal risky share depending on the cash-on hand. Based on these functions, one can obtain the value function for the second to last period. Thus, to get the solutions for all of the remaining periods, one iterates backwards from the last to the first period.

Unfortunately, there is no analytical solution for the agent's optimization problem due to the stochastic nature of labor income and stock returns. Hence, I solve the model numerically. In practice, to reduce computational load I construct a discrete grid of next period's possible cash-on-hand levels depending on income shocks and asset returns.

[2]https://www.pewresearch.org/fact-tank/2020/04/24/not-all-unemployed-people-get-unemployment-benefits-in-some-states-very-few-do/

Based on the grid, I calculate the optimal consumption and risky share for a given level of wealth. Finally, the grid points are interpolated to construct the consumption function and the policy function for the optimal risky share[3].

C Simulated Method of Moments

C.1 Covariance Matrix of Moments

Following Catherine (2022), I aggregate the moments from the SCF data by cohort and year. Then, I bootstrap the data to obtain a sample of 1000 vectors of moments. Using these bootstrapped moments, I calculate the covariance matrix of moments.

C.2 Estimation process

In the first (global) stage of the estimation process, I simulate a sample of 4000 agents who receive varying income, unemployment, and mortality shocks. Furthermore, they start with varying levels of income and wealth. Each agent is simulated for 3200 periods, where each agent that dies is newborn again and receives a new level of initial income, wealth, and income shocks. Hence, cohort and year effects are no concern in the simulated data. I simulate the model for 2500 quasi-random vectors of parameters. The estimated moments are then the averages for wealth, risky share, conditional risky share, and participation rate in each three-year age group. In the second stage, I use the Nelder-Mead algorithm (Nelder & Mead, 1965) to run local optimizations on the first stage estimates. I choose the 10 best estimates from the first stage estimates and make sure they converge to the same point.

[3]For setting up and solving the model, I utilize and extend the *Heterogeneous Agents Resources and toolKit (HARK)* by Carroll et al. (2018).

Chapter IV

Populist Voting as Insurance against Perceived Labor Income Risk

Abstract

The recent success of populist politicians in Europe and the USA is difficult to explain via economic and financial motives. I propose that individuals vote for populist parties to insure against perceived future labor income risk. Right-wing populist parties promise to reduce labor market competition by limiting immigration and the influence of globalization. Left-wing populist parties support policies that expand the social safety net. I find that the perceived size of potential labor income shocks increases the likelihood of voting for a right-wing populist whereas the perceived likelihood of labor income shocks increases left-wing populist voting. However, the channels proposed in the literature like anti-immigration attitudes or a backlash against globalization bear little explanatory power for this correlation. Overall, I find little support for economic explanations of populist voting.

1 Introduction

Right-wing populist parties are on the rise in the Western world for the past decade (Rooduijn, 2018). Researchers in economics and finance scramble to understand this trend as classical economic explanations seem to bear little explanatory power (Margalit, 2019). Populist landmark victories like the Brexit or the election of Donald Trump as president of the USA occurred after years of steady economic growth and low levels of unemployment. Furthermore, it is unclear why voters would vote for right-wing rather than left-wing populist parties when confronted with high economic insecurity. Hence, alternative explanations have been broad forward like a backlash of the "losers" of globalization (Colantone & Stanig, 2018) or anti-immigration attitudes in response to domestic labor market competition due to immigration (Guiso et al., 2017). The rise of populist parties is problematic as their economic policies tend to have far-reaching consequences for a countries' economy and thereby household's finances (Guriev & Papaioannou, 2022). One should think of populist economic policies as "the implementation of policies receiving support from a significant fraction of the population, but ultimately hurting the economic interests of this majority." (Acemoglu et al., 2013). Hence, it is important for researchers to understand the antecedents of populist voting.

In this paper, I propose that populist voting can be interpreted as attempt of households to reduce their perceived labor income risk. This idea encompasses or is implicit in other explanations for right-wing populist voting mentioned earlier. Globalization induces foreign competition in domestic markets and thereby increases the risk of unemployment. Similarly, immigration introduces domestic labor market competition which might endanger workers' jobs. Populist parties often promise to address these concerns. On the one hand, right-wing populist parties promise to limit immigration and thereby eliminating competition of foreign labor which could reduce the perceived threat of jobloss. Similarly, right-wing populist parties propagate isolationist economic policies which curbs competition by cheap foreign products and again might result in a reduced perceived jobloss likelihood. On the other hand, left-wing populist parties promote the expansion of the welfare state and redistributive policies which directly insure individuals against disaster labor income shocks via more generous unemployment benefits.

My paper makes three important contributions. First, I propose a new economic mechanism for populist voting which is insurance against future labor income risk. This mechanism is implicit in previously hypothesized channels and a rejection of this channel might also challenge other economic explanations. Second, I explore the economic antecedents of populist voting on an individual level. This contrasts with previous economics papers on populism that mostly explore voting outcomes on a regional level (e.g. David et al., 2013; Guiso et al., 2019; Pástor & Veronesi, 2021). Third, I investigate left-wing and right-wing populist voting separately and propose a potential economic mechanism through which voter decide whether to vote for a right-wing or left-wing populist party. This is novel as previous papers in economics either only focus on right-wing populist voters or pool populist parties across the political spectrum and thereby disregard varying underlying motives for voting for opposite ends of the political spectrum.

In this paper, I employ four proxies for task-specific human capital to measure the perceived *size* of potential future labor income disaster shocks and unemployment beliefs as a measure of the perceived *likelihood* of the labor income disaster shocks. Taking together size and likelihood of labor income disaster shocks measures an individual's labor income disaster risk. I make use of three large, long-running household panels that cover a representative sample of the German, Dutch, and Swiss population. These three countries vastly differ in their political landscape which increases the generalizability of the findings. First, I find that individuals with more task-specific human capital are significantly more likely to vote for right-wing populist parties. A one standard-deviation increase in task-specific human capital increases the probability of voting for a right-wing populist party by around 10 to 20 percent. Conversely, the effect of the size of labor income shocks is a lot less pronounced for left-wing populist voting.

Second, I test whether unemployment beliefs affect the likelihood of voting for a populist party. In contrast to the size of the labor income shock, the perceived likelihood does not influence the probability of a right-wing vote. However, individuals with more pessimistic unemployment beliefs are significantly more likely to vote for a left-wing populist party. On average, a one standard-deviation increase in unemployment beliefs increases the likelihood of a left-wing populist vote by a considerable 25 percent across all three countries. Third, I regress populist voting on the interaction between the perceived size of the labor income shock and the perceived probability of the labor income shock. This analysis clarifies the relationship between perceived labor income risk and the decision whether to vote for a right-wing or left-wing populist party. I find that individuals are *less* likely to vote for right-wing populist parties if they have high task-specific human capital and pessimistic unemployment beliefs, but they are *more* likely to vote for left-wing populist parties.

Overall, these findings are in line with the interpretation that voters vote for right-wing populist parties to address diffuse threats of distant disaster labor income shocks. Examples for this could be labor competition from immigrants or foreign competition of cheap products due to globalization. Yet, as soon as there is a concrete threat of a negative labor income shock they turn to left-wing populist parties that promise to soften the blow of unemployment through a more generous social safety net. Hence, I explore further whether indeed the channel through which the size of the labor income shock affects right-wing populist voting and the likelihood of labor income shocks affects left-wing populist voting is the motivation to reduce future labor income risk.

The two channels proposed in the economics and finance literature through which perceived labor income risk affects right-wing populist voting are negative immigration attitudes (e.g. Scheve & Slaughter, 2001; Guiso et al., 2017) and a backlash against globalization (e.g. David et al., 2013; Pástor & Veronesi, 2021). First, I demonstrate that individuals with more task-specific human capital exhibit more concerns about immigration which is in line with Pardos-Prado and Xena (2019). However, a meditation analysis shows that this channel has no explanatory power for the impact of perceived labor income risk on right-wing populist voting. Thus, I turn to the threat of globalization as potential channel. I utilize import competition from china (Colantone & Stanig, 2018) as exogenous variation in exposure to globalization to test whether more exposed individuals are more likely to vote for right-wing populist parties when they have higher task-specific human capital. Even though a larger exposure to import shocks increases the likelihood to vote for a right-wing populist party, there is no evidence that this depends on an individual's perceived labor income risk. Again, this contradicts the hypothesis that right-wing populist voting is perceived as insurance against labor income shocks.

It is more difficult to directly test whether left-wing populist voters view their vote as insurance against future labor income shocks. Yet, I can identify subsets of the population that should be particularly inclined to reduce their labor income risk from a theoretical point of view. Thus, I test whether more financially fragile individuals are more likely to vote for left-wing populist parties as their perceived probability of unemployment increases. However, I find no evidence that individuals with less precautionary savings and a lower saving rate are more likely to vote for a left-wing populist party. Furthermore, more risk averse individuals should be also more willing to vote for a left-wing populist party to address increases in labor income risk. Yet, there is again only limited evidence that more risk-averse voters have a higher probability of voting for a left-wing populist party as their perceived unemployment probability increases.

In conclusion, the results suggest that populist voting is correlated with an individual's perceived labor income risk. Furthermore, beliefs about the near future seem to determine whether an individual turns to a right-wing or left-wing populist party. However, there is little evidence that populist voting is indeed perceived as insurance against future labor income disaster risk. Individuals with more task-specific human capital are not affected by immigration attitudes or the threat of globalization when deciding to vote for a right-wing populist party. Similarly, individuals with a higher perceived likelihood of jobloss are not more likely to vote left-wing populist parties when facing more disastrous outcomes. Hence, economic explanations proposed in the literature cannot explain the correlation between labor income risk and populist voting.

This paper is structured as follows. Section 2 discusses the related literature in finance and economics and introduces the theoretical framework I have in mind. Section 3 describes the data and methodology employed in the paper. Section 4 presents the empirical findings and explores the potential channels. Finally, section 5 concludes.

2 Related Literature and Theoretical Framework

2.1 Related Literature

I contribute to the emerging literature that explores how a household's financial situation affects populist voting. The two most salient issues discussed by populist parties is rising inequality in society due to globalization (e.g. Colantone & Stanig, 2019) and rising levels of immigration (e.g. Margalit, 2019). The academic literature has focused on both of these channels. In the following, I summarize the arguments and discuss the relevant papers in these strands of literature.

One strand of the academic literature explores how globalization induces populist voting due to the backlash to globalization and the associated "losers of globalization". These papers assert that trade shocks since the early 1990s, like China joining the WTO, has lead to competition from cheap labor abroad and cheap products at home (David et al., 2013). Thus, parts of the population face significant lower wages or even unemployment due to the structural transformation of the economy (Acemoglu et al., 2016). In particular, the manufacturing sector has been hit the hardest because of competition from cheap Chinese labor. On the flip side, well-educated, more flexible workers as well as owners of capital have massively profited from this development. Thus, globalization has created winners and losers and exacerbated economic inequality in Western societies. The literature argues that this trend intensified resentment among the "losers" against the profiting "winners". Right-wing populist parties have stepped in and promoted increasing economic protectionism against foreign competition.

Following this argument, Colantone and Stanig (2018) exploit regional variation across Europe in the import competition from China to measure how hard a region is hit by globalization. They find that more foreign competition in a particular region is associated with an increase in support for nationalist, isolationist, and right-wing parties. These findings are in line with the argument that globalization has led to a populist backlash among the "losers". Similarly, Autor, Dorn, Hanson, and Majlesi (2020) show that increased import competition across US districts has led both to a rightward shift of the electorate as well as an increase in polarization across voters. Finally, Pástor and Veronesi (2021) develop an equilibrium model of populist voting in which voters optimally vote for populist parties in response to increasing levels of inequality within society. In their model, populist parties promise to end globalisation and thereby reduce inequality. They find theoretically and empirically that countries with higher inequality and trade deficits have a higher share of votes for populist parties.

Another strand of the literature has explored how rising levels of immigration to Western democracies induces right-wing populist voting. In classic labor economics, immigration is foremost seen as labor market competition to domestic workers (Scheve & Slaughter, 2001). Following this argument, workers of a country should feel mostly threatened by immigrants at a similar skill level as themselves. Hence, theory predicts that low-skilled domestic workers should primarily oppose low-skilled and high-skilled workers should oppose high-skilled immigration. However, several recent studies show that citizens of a country tend to oppose immigration of low-skilled workers and view immigration of high-skilled individuals as more favorable irrespective of their own skill level (Citrin et al., 1997; Hainmueller & Hiscox, 2010; Hainmueller & Hopkins, 2015).

Pardos-Prado and Xena (2019) propose a different interpretation of how the threat of immigration might induce populist voting. They argue that one needs to consider labor demand rather than actual labor supply in the form of immigrants when exploring how opposed someone is to immigration. More specifically, workers with highly specific skills that make it difficult to find an alternative job should be more opposed to immigration, which might threaten their job. Indeed, the authors find that individuals with higher job specificity, i.e. higher task-specific human capital, are more concerned about immigration. Yet, they do not explore the impact on populist voting behavior.

In this paper, I argue that voting for populist parties could be perceived by households as insuring against labor income shock both by reducing the likelihood of unemployment shocks as well as the size of the impact if a shock hits. I explore this argument in more detail in the next subchapter. This idea is closely related to the paper by Guiso et al. (2017). They argue that populist parties advocate protectionist policies which appear attractive to voters in times of economic uncertainty. Moreover, they argue that economic insecurity also has indirect effects on populist voting through trust in political institutions and mistrust towards immigrants. My paper differs in how I measure economic insecurity. The authors use objective measures like past unemployment or the exposure to globalization whereas I use a subjective measure capturing the perceived economic insecurity, which should more directly elicit voters' feelings. Furthermore, Guiso et al. (2017) do not consider left-wing and right-wing populist parties separately. Hence, my paper goes beyond that initial idea and establishes one channel through which a voter decides whether to vote for a left-wing or right-wing populist party.

2.2 Theoretical Framework

In this part, I flesh out the argument why populist voting could be perceived by households as reducing their labor income disaster risk. Labor income disaster risk has two dimensions: The size of the shock as well as the probability of the shock. The most salient labor income shock a household can experience is unemployment. Given a household experiences such a unemployment shock, the magnitude of the labor income risk is crucially determined by the difficulty of finding a new job and the reduction in labor income incurred by accepting a new job. Both of these factors are affected by a worker's task-specific human capital (Gibbons & Waldman, 2004). More task-specific human capital makes it more difficult to find a new job and induces potential wage cuts. The second dimension that determines labor income disaster risk is the probability of experiencing an unemployment shock. Taken together, the size of the labor income shock and its probability jointly determine the household's labor income risk.

Right-wing and left-wing populist parties both promise a reduction in labor income risk to the electorate. Right-wing populist parties advocate limiting immigration and thereby insulating workers against labor supply shocks. Similarly, these parties propagate isolationist policies which curb competition to domestic firms. Hence, they promise to reduce the probability of labor income shocks and at the same time might limit the size of the shocks by reducing the domestic labor competition. Conversely, left-wing populist parties typically support redistributing wealth, expanding the welfare state, and increasing worker protection rights. Thus, they offer insurance against labor income shocks by reducing the size of income shocks due to expanded unemployment benefits and reduce the likelihood of labor income shocks due to increased worker protection. Ex-ante it is an empirical question which approach of the political spectrum voters favor and whether this is context-dependant.

3 Data and Methodology

I employ data from three well established and long running European household panels in my analyses: the German Socio-Economic Panel (GSOEP), the Swiss Household Panel (SHP), and the Longitudinal Internet studies for the Social Sciences (LISS) panel in the Netherlands. My main independent variable is a dummy variable that elicits an individual's preference for a populist party. In line with Van Kessel (2015), I define the *Alternative für Deutschland (AfD)*, the *Partij voor de Vrijheid (PVV)*, and the *Schweizer Volkspartei (SVP)* as right-wing populist parties[1]. For the left-wing populist parties, the cutoff is not as clear as for the right-wing populist parties. I determine *Die Linke*, *Socialistische Partij (SP)*, and the *Partei der Arbeit Schweiz (PdAS)* as left-wing populist party as a central theme of their platform is the struggle of the people against some kind of political and economic elite.

Following Pardos-Prado and Xena (2019), I measure the task-specificity of an occupation using four measures. The compartmentalization of occupational tasks within major occupational groups (Iversen & Soskice, 2001), occupational unemployment rates (Rehm, 2009), occupational specific experience (Kambourov & Manovskii, 2009), and occupational permanency (Pardos-Prado & Xena, 2019). First, compartmentalization of occupational tasks within major occupational groups is defined as share of International

[1] I include the *AfD* myself as they are not analysed by Van Kessel (2015). For completeness, I also include *Lega dei Ticinesi*, *Freiheits-Partei der Schweiz (FPS)*, *Schweizer Demokraten (SD)*. However, they have very little following and excluding them does not affect the results.

Standard Classification of Occupations (ISCO-88) unit groups over the total number of unit groups in a major occupational cluster, divided by the share of the workforce that the major group represents. Intuitively, a high numerator signifies that there are highly specific tasks within an occupation. A low denominator implies that these tasks are performed by a small percentage of the overall population. Second, occupational unemployment rate is measured as the percentage of individuals unemployed in an ISCO-88 major group. This measure proxies for the difficulty of finding a new job within one's occupation. Third, occupation-specific work experience is the average number years within a ISCO-88 major group an individual has worked for the same employer. This variable proxies for the rigidity of the labor market within occupation. Finally, occupational permanency or occupational transition rates is the percentage of individuals within a two-digit ISCO occupation that remains in that occupation from one year to the next. Intuitively, this measures the difficulty of changing jobs within an occupation. Unfortunately, information on household's occupation is not available in the Dutch survey.

Figure IV.1: This figure shows the average compartmentalization of occupational tasks (left) and occupation specific experience (right) of the two highest and lowest ISCO-88 major groups in Germany (top) and Switzerland (bottom).

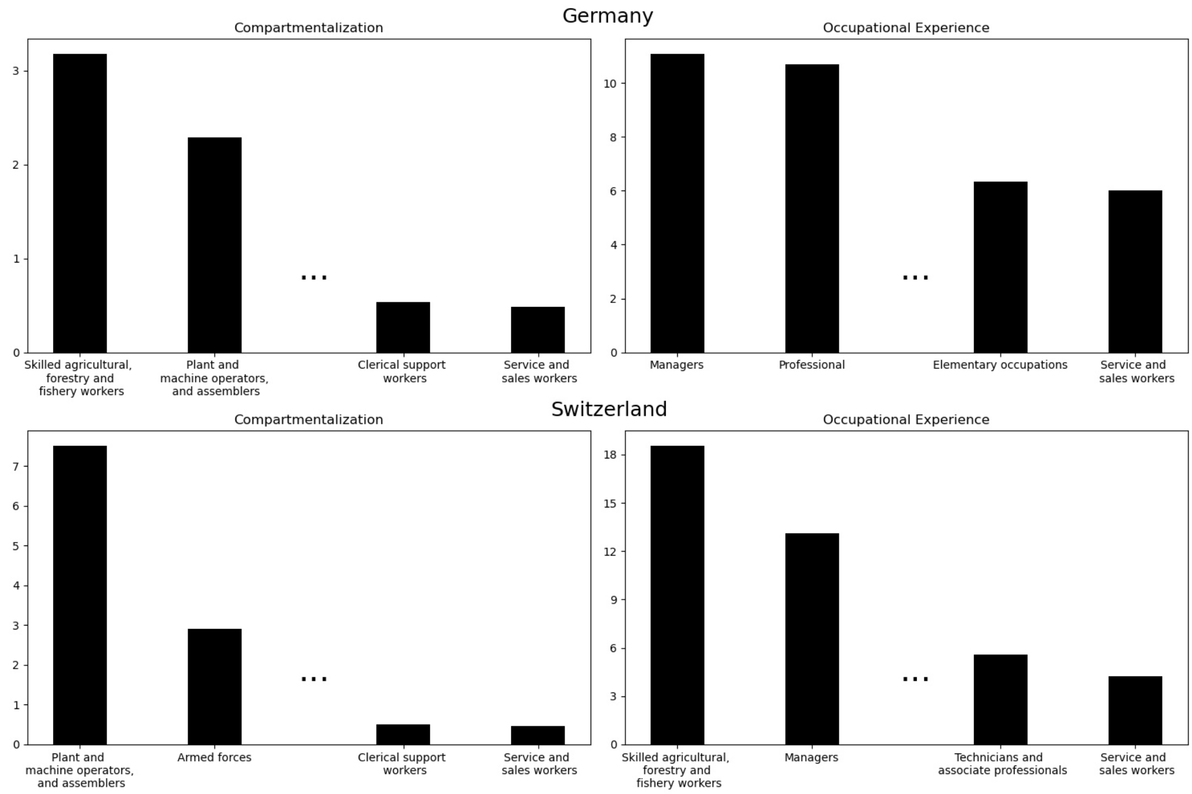


Figure IV.1 shows the ISCO-88 major groups with the highest and lowest level of compartmentalization of occupational tasks and occupation specific experience. Comparing Germany and Switzerland demonstrates that similar occupational groups, like plant and machine operators, have high task-specific human capital whereas for example service and sales workers tend to have less task-specific human capital. Additionally, I introduce a measure of the perceived likelihood of the labor income disaster shock materializing. I utilize the question *"What is the probability of losing your job within the next 12 months?"* with the answers to this question ranging from 0 to 100 percent. This is a direct measure of unemployment beliefs as a value of 1 represents absolute certainty of jobloss whereas a value of 0 represents absolute perceived job security.

To elicit immigration attitudes, I use different questions for each of the panels. In Germany, people are asked how concerned they are about immigration, in Switzerland whether there should be equal opportunities for foreigners or whether natives should be favored, and in the Netherlands they are asked whether they think that there are too many foreigners in the country. Each question is then scaled to be a dummy variable with a value of 1 if an individual holds more hostile attitudes towards immigration. Moreover, I include several demographics as control variables: gender, age, income, education, and employment status. Specifically, income is measured as the monthly net income, education is a dummy variable that equals one if an individual holds an university degree, and employment status is a dummy variable that equals one if one is unemployed.

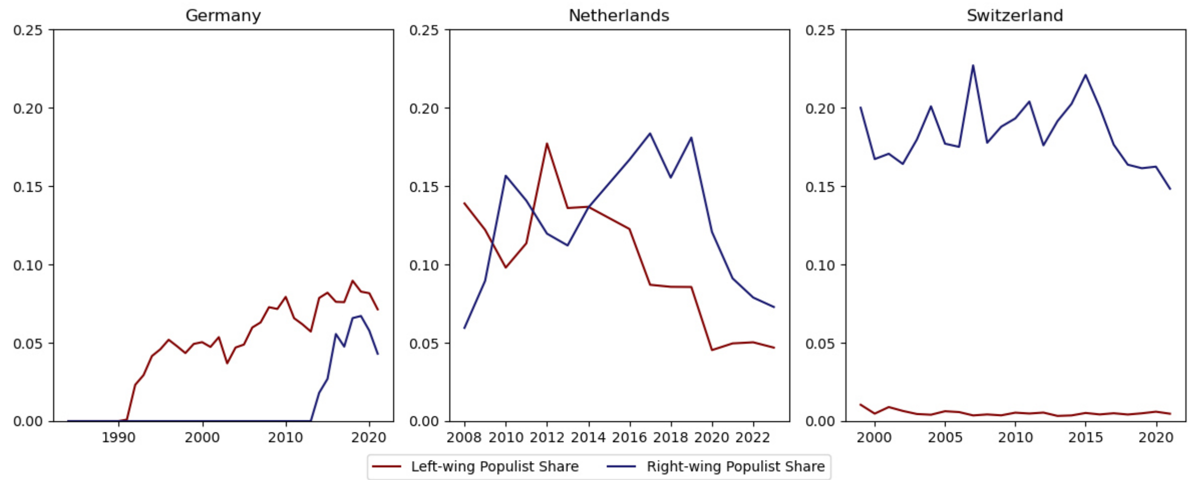
Table 1 shows descriptive statistics for the main variables of interest for each of the three panels separately. The three panels utilized in this study aim to survey representative samples of the countries' respective population. Hence, the demographic variables look as expected with roughly half of participants being female, an average age of around 40 and an mean net income ranging from 2700 EUR in Germany to 4800 CHF in Switzerland. One of the main variable of interest is unemployment beliefs measured as the perceived probability of losing one's job. Intriguingly, the estimated mean probability is the roughly the same across countries with an average value of 19 percent. Regarding voting behavior, only 7 percent of German individuals state a preference for a populist

Table IV.1: This table shows the mean, median, and standard deviation for the main variables employed in this paper. Income is the monthly income in the respective currency. Education is an indicator variable equal to one if the individual holds an university degree. Similarly, unemployed is an indicator variable equal to one if the individual is unemployed. Immigration concern is an indicator variable if the individual reports concerns about immigration. For details regarding regarding the exact variable definitions please refer to appendix A.

	Germany			Switzerland			Netherlands		
	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.
Female	0.52	1.00	0.50	0.51	1.00	0.50	0.51	1.00	0.50
Age	46.59	46.00	17.56	40.78	42.00	22.61	40.18	41.00	22.24
Income	2689.80	2250.00	4272.67	4835.57	4191.67	4953.47	3435.01	3000.00	6359.46
Education	0.13	0.00	0.34	0.15	0.00	0.36	0.14	0.00	0.35
Unemployed	0.07	0.00	0.26	0.01	0.00	0.11	0.02	0.00	0.15
Immig. concern	0.28	0.00	0.45	0.14	0.00	0.34	0.40	0.00	0.49
Difficulty find job	0.18	0.00	0.39	.	.	.	0.45	0.00	0.50
Unemp. beliefs	0.19	0.10	0.25	0.19	0.10	0.24	0.17	0.05	0.26
Compartment.	1.00	0.80	0.59	1.00	0.74	1.12	.	.	.
Occupational unemp.	0.02	0.01	0.02	0.00	0.00	0.00	.	.	.
Occupation spec. exp.	8.95	9.85	3.11	7.02	6.50	4.40	.	.	.
Transition rate	0.69	0.70	0.12	0.92	0.93	0.06	.	.	.
Populist party	0.07	0.00	0.25	0.19	0.00	0.39	0.23	0.00	0.42
Right-wing populists	0.01	0.00	0.11	0.18	0.00	0.39	0.12	0.00	0.33
Left-wing populists	0.05	0.00	0.23	0.01	0.00	0.07	0.11	0.00	0.31

party, whereas this rises to 19 percent in Switzerland and 23 percent in the Netherlands. This is in line with right-wing populism being a more recent phenomenon in Germany while right-wing populists have been firmly established in the Netherlands and even representing the governing party in Switzerland. Furthermore, the very high percentage in the Netherlands stems from a strong left-wing populist party as well as methodological differences. In Germany, participants are asked with which party they identify, whereas in the Dutch panel they are asked which party they would vote for if there was an election this weekend. As many vote for populist parties out of protest, they might not necessarily identify with that party, which leads to lower reported percentages.

Figure IV.2: This figure shows the share of votes for right-wing populist parties in blue and left-wing populist parties in red over the respective sample period.



Furthermore, figure IV.2 plots the left-wing and right-wing populist voting share over time in red and blue, respectively. The leftmost panel displays the populist voting share in Germany. *Die Linke* formerly known as *PDS* has been a relevant force in German politics since reunification especially in Eastern Germany. Conversely, the right-wing populist party *AfD* is a more recent phenomenon being founded in 2013 as eurosceptic party but experiencing a lot of electoral success in recent years. Contrarily, the political landscape in the Netherlands is more fragmented and both right-wing and left-wing populists have been vastly successful. Finally, the right panel demonstrates that left-wing populists play barely any role in Swiss politics. Yet, the right-wing populist *SVP* has been the strongest

Swiss party for several years now.

For most analyses, I conduct fixed effect OLS regressions. Specifically, I include year fixed effects to control for variation solely attributable to time effects. This leads to the following regression model:

$$Y_{it} = \beta X_{it} + \delta_t + \epsilon_{it}$$

where Y_{it} represents my dependent variable of interest, namely populist voting behavior. X_{it} is the vector of independent variables that vary on an individual level over time. Finally, δ_t are the year fixed effects, and ϵ_{it} the error term. Standard errors are clustered on person level to account for the auto-correlation over time. Unfortunately, it is not possible to account for person fixed effects to elicit the within person change in voting behavior in response to changes in perceived labor income risk. Voting behavior and the proxies of task-specific human capital barely vary on an individual level. Hence, including person fixed effects would effectively result in most observations dropping out.

4 Empirical Results

4.1 Task-specific Human Capital and Populist Voting

First, I explore how task-specific human capital affects the likelihood to vote for a populist party. For that purpose, I regress a populist voting dummy on the four previously discussed measures of skill specificity and several demographics. The regression includes year fixed effects as well as standard errors clustered on individual level to account for the high persistence of voting preferences. I run these regression for Germany and Switzerland separately. Table IV.2 and table IV.3 show the results for Germany and Switzerland, respectively.

Interestingly, the results of the regression are not as straightforward as one would expect. Columns 1 to 4 of table IV.2 demonstrate that the perceived size of the labor income shock seems to affect the likelihood to vote for a populist party. However,

Table IV.2: This table shows the results of regressing a populist voting indicator variable as well as right-wing and left-wing populist voting indicators on various proxies for the size of labor income disaster shocks using the German Socio-Economic Panel. Furthermore, I control for individual characteristics. I estimate OLS regressions with year fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Populist Party	Populist Party	Populist Party	Populist Party	Right-wing Populists	Right-wing Populists	Right-wing Populists	Right-wing Populists	Left-wing Populists	Left-wing Populists	Left-wing Populists	Left-wing Populists
Compartment.	0.013***				0.005***				0.008***			
	(4.62)				(5.02)				(3.09)			
Occupational unemployment		0.376***				0.077**				0.299***		
		(3.96)				(2.38)				(3.30)		
Occupational experience			-0.005***				-0.001***				-0.004***	
			(-4.59)				(-3.97)				(-3.54)	
Transition rates				-0.012				-0.003				-0.009
				(-1.18)				(-1.11)				(-0.92)
Female	0.000	-0.004	-0.005	-0.003	-0.004***	-0.006***	-0.006***	-0.006***	0.004	0.002	0.001	0.002
	(0.02)	(-1.30)	(-1.60)	(-1.02)	(-6.09)	(-8.03)	(-8.31)	(-7.72)	(1.36)	(0.51)	(0.27)	(0.73)
Age	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(-0.35)	(-0.33)	(-0.17)	(-0.08)	(0.08)	(0.30)	(0.43)	(0.49)	(-0.38)	(-0.41)	(-0.29)	(-0.21)
Education	0.047***	0.048***	0.052***	0.046***	-0.007***	-0.007***	-0.007***	-0.008***	0.054***	0.055***	0.058***	0.054***
	(8.38)	(8.57)	(8.74)	(8.17)	(-9.40)	(-9.03)	(-7.82)	(-9.69)	(9.80)	(9.96)	(9.95)	(9.64)
Net Income (monthly)	-0.053***	-0.052***	-0.053***	-0.054***	-0.003***	-0.002***	-0.002***	-0.003***	-0.051***	-0.050***	-0.051***	-0.051***
	(-17.00)	(-16.54)	(-16.53)	(-17.19)	(-3.52)	(-3.34)	(-2.94)	(-3.91)	(-16.59)	(-16.16)	(-16.23)	(-16.70)
Unemployed	0.062***	0.057***	0.059***	0.062***	0.002	0.001	0.001	0.002	0.060***	0.056***	0.058***	0.060***
	(4.50)	(4.09)	(4.19)	(4.45)	(0.62)	(0.26)	(0.31)	(0.56)	(4.44)	(4.13)	(4.21)	(4.41)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	74922	74922	72351	74888	74922	74922	72351	74888	74922	74922	72351	74888
Adjusted R^2	0.041	0.041	0.039	0.040	0.044	0.043	0.043	0.043	0.031	0.031	0.029	0.030

t statistics in parentheses

compartmentalization of occupational tasks and occupational unemployment have a statistically significant positive impact on the likelihood to vote for a populist party whereas occupational experience has a statistically significant negative impact. A one standard deviation increase in the compartmentalization variable increases the likelihood to vote for a populist party by 0.8 percentage points. Similarly, a one standard deviation increase in occupational unemployment increases the probability of voting for a populist party by 0.8 percentage points as well. Given that the unconditional probability of voting for a populist party in the sample is 6.7 percent, the size of the effect is considerable.

Exploring the impact of the size of the labor income disaster shock on right- and left-wing populist voting separately reveals that there appears to be little difference for both ends of the political spectrum. Again, compartmentalization of occupational tasks and occupational unemployment have a statistically significant positive impact whereas occupational experience has a statistically significant negative impact on the probability to vote for a right- and left-wing party. Given that the unconditional probability of voting for a right-wing populist party is 1.3 percent and 5.4 percent for a left-wing party, a one standard deviation increase in the compartmentalization variable increases the likelihood to vote for a right-wing party by 22 percent. Conversely, the same increase in compartmentalization only increases the probability to vote for a left-wing populist party by 8.5 percent.

Neither age nor gender has any significant influence on the overall probability of voting for a populist party. Yet, in line with previous literature, being female significantly decreases the likelihood to vote for a right-wing populist party whereas it has a slightly positive effect on voting for a left-wing populist party. Effectively, being female reduces the probability to vote for a right-wing populist party by one third. However, having a university degree greatly increases the probability of voting for populist party. This is due to a disproportional amount of university degree holders identifying with *Die Linke* in Germany. Similarly, being unemployed increases the likelihood to vote for a populist party by around 6 percentage points which again is mostly due to *Die Linke* voters. Finally, monthly income has a highly significant negative impact across the board on both left-wing and right-wing populist voting.

Conducting the same analyses for Switzerland provides a clearer picture. Table IV.3 displays the findings. Compartmentalization of occupational tasks, occupational unemployment, and occupation specific experience have a highly statistically significant positive impact on the likelihood to vote for a populist party. A one standard deviation increase in any of these measures increases the likelihood to vote for a populist party by 2.8 to 3.7 percentage points. Given that the unconditional probability of voting for a populist party in Switzerland is 18.9 percent, the economic magnitude of the impact is slightly larger. In Germany, a one standard deviation increase in these measures increases the likelihood by around 12 percent compared to the unconditional probability, whereas in Switzerland this ranges from 14 to 20 percent. Finally, job transition rates again have no significant impact. Considering the very different settings, it is astonishing that the effect of the various measures of job specificity have such a comparable impact on populist voting.

Contrary to the previous findings, the results are purely driven by right-wing populist voting behavior. The political landscape in Switzerland is dominated by the right-wing populist party *SVP* which has the most seats in the Swiss parliament since 1999. Left-wing populist parties play barely any role which also translates into an unconditional probability of voting for such a party of 0.5 percent. Therefore, it is not clear whether the lack of statistical significant impact of task-specific human capital on left-wing populist voting is due to a lack of evidence or a lack of statistical power. Hence, gender and education have a strong negative impact on voting for a populist party in the Swiss sample. Female voters and individuals with university degree typically shun right-wing parties. Similar to the German results, age has no influence on the probability to vote for a populist party.

In conclusion, these findings indicate that there is a positive relationship between the potential size of labor income shocks and the probability to vote for a populist party. Nevertheless, the results are not consistent for all measures of task-specific human capital. Furthermore, the impact of task-specific human capital is the most pronounced for right-

Table IV.3: This table shows the results of regressing a populist voting indicator variable as well as right-wing and left-wing populist voting indicators on various proxies for the size of labor income disaster shocks using the Swiss Household Panel (SHP). Furthermore, I control for individual characteristics. I estimate OLS regressions with year fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Populist Party	Populist Party	Populist Party	Populist Party	Right-wing Populists	Right-wing Populists	Right-wing Populists	Right-wing Populists	Left-wing Populists	Left-wing Populists	Left-wing Populists	Left-wing Populists
Compartment.	0.034***				0.034***				-0.000			
	(8.44)				(8.54)				(-1.23)			
Occupational unemployment		9.435***				9.418***				0.017		
		(10.55)				(10.55)				(0.12)		
Occupational experience			0.007***				0.007***				-0.000	
			(5.28)				(5.41)				(-0.97)	
Transition rates				0.019				0.019				-0.000
				(0.37)				(0.37)				(-0.01)
Female	-0.070***	-0.085***	-0.078***	-0.086***	-0.069***	-0.084***	-0.079***	-0.084***	-0.001	-0.001	0.001	-0.001
	(-10.02)	(-12.21)	(-6.51)	(-12.03)	(-9.94)	(-12.15)	(-6.72)	(-11.96)	(-0.89)	(-0.79)	(0.36)	(-0.85)
Age	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000	-0.001	-0.000	0.000	0.000	-0.000	0.000
	(-1.25)	(-1.46)	(-1.35)	(-0.82)	(-1.33)	(-1.53)	(-1.18)	(-0.93)	(0.45)	(0.43)	(-0.94)	(0.68)
Education	-0.158***	-0.165***	-0.147***	-0.170***	-0.163***	-0.170***	-0.154***	-0.174***	0.005***	0.005***	0.007*	0.005***
	(-25.49)	(-26.63)	(-13.85)	(-26.97)	(-26.87)	(-28.06)	(-15.67)	(-28.34)	(3.06)	(3.19)	(1.65)	(3.05)
Net Income (monthly)	-0.020***	-0.017***	-0.018***	-0.021***	-0.018***	-0.015***	-0.018***	-0.020***	-0.002***	-0.002***	0.000	-0.002***
	(-5.39)	(-4.53)	(-2.77)	(-5.69)	(-4.94)	(-4.08)	(-2.82)	(-5.25)	(-2.78)	(-2.76)	(0.17)	(-2.75)
Unemployed	0.022	0.011	0.066	0.027	0.016	0.004	-0.001	0.025	0.006	0.006	0.067	0.002
	(0.79)	(0.38)	(0.83)	(0.97)	(0.58)	(0.16)	(-0.01)	(0.89)	(0.88)	(0.87)	(1.31)	(0.40)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	72,864	72,864	101,42	70,367	72,864	72,864	10,142	70,367	72,864	72,864	10,142	70,367
Adjusted R^2	0.061	0.057	0.040	0.054	0.064	0.060	0.044	0.056	0.001	0.001	0.003	0.001

t statistics in parentheses

wing populist voting whereas there is only partial evidence that it affects the probability of left-wing populist voting. In the next section, I investigate whether the perceived likelihood of labor income disaster shocks affects populist voting.

4.2 Unemployment Beliefs and Populist Voting

Next, I explore the impact of the likelihood of labor income disaster shocks on populist voting behavior. For that purpose, I regress indicator variables for overall, right-wing, and left-wing populist voting on the perceived unemployment probability and control variables. Table IV.4 displays the results of these regressions for Germany, Switzerland, Netherlands, and a sample including all three countries.

Columns 1 to 3 show the result for Germany. Overall, more pessimistic unemployment beliefs translate into higher propensity to vote for a populist party. However, this coefficient is purely driven by left-wing populist voters. A one standard deviation increase in the perceived likelihood of jobloss increases the probability to vote for a left-wing populist party by 1.25 percentage points. Conversely, there is no impact on the likelihood to vote for a right-wing populist party.

The results are similar for the Netherlands. Again, unemployment beliefs have a highly statistically significant impact on the likelihood to vote for a populist party. This coefficient is again completely driven by left-wing populist voting. A one standard deviation increase in unemployment beliefs increases the likelihood of voting for a left-wing populist party by around 2 percentage points. Comparing Germany and Netherlands shows that a one standard deviation increase in unemployment beliefs increases the unconditional probability of left-wing populist voting by around 25 percent.

Columns 4 to 6 display the findings for Switzerland. Contrary to the other two countries, unemployment beliefs have a strong negative impact on populist voting. However, pooling right-wing and left-wing parties hides considerable heterogeneity. This result is driven by right-wing populist voters. More pessimistic unemployment beliefs have a statistically significant positive influence on the probability to vote for a left-wing populist party. Interestingly, a one standard deviation increase in unemployment beliefs increases

Table IV.4: This table shows the results of regressing a populist voting indicator variable as well as right-wing and left-wing populist voting indicator variables on unemployment beliefs in Germany, Netherlands, and Switzerland. Furthermore, I control for individual characteristics. I estimate OLS regressions with year fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Germany			Switzerland			Netherlands			All		
	Populist Party	Right-wing Populists	Left-wing Populists	Populist Party	Right-wing Populists	Left-wing Populists	Populist Party	Right-wing Populists	Left-wing Populists	Populist Party	Right-wing Populists	Left-wing Populists
Unemployment Beliefs	0.050***	-0.001	0.051***	-0.049***	-0.053***	0.004**	0.093***	0.017	0.077***	0.003	-0.031***	0.034***
	(7.43)	(-0.53)	(7.96)	(-5.08)	(-5.59)	(2.08)	(4.88)	(1.11)	(5.05)	(0.43)	(-5.53)	(10.98)
Female	-0.006	-0.010***	0.004	-0.087***	-0.087***	-0.001	-0.043***	-0.060***	0.017*	-0.058***	-0.057***	-0.001
	(-1.46)	(-8.14)	(1.11)	(-12.62)	(-12.59)	(-0.67)	(-3.43)	(-5.78)	(1.85)	(-13.50)	(-14.44)	(-0.45)
Age	0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.001***	0.002***	0.000	-0.000	0.000***
	(0.52)	(0.40)	(0.40)	(-1.21)	(-1.28)	(0.42)	(0.46)	(-3.35)	(4.48)	(1.15)	(-0.95)	(5.77)
Education	0.041***	-0.012***	0.053***	-0.170***	-0.175***	0.005***	-0.165***	-0.133***	-0.033***	-0.100***	-0.116***	0.016***
	(6.95)	(-10.06)	(9.19)	(-27.86)	(-29.32)	(3.32)	(-12.47)	(-15.40)	(-3.02)	(-22.88)	(-31.44)	(6.65)
Net Income (monthly)	-0.061***	-0.008***	-0.053***	-0.021***	-0.019***	-0.002***	-0.115***	-0.037***	-0.078***	-0.032***	-0.017***	-0.015***
	(-15.93)	(-6.74)	(-14.53)	(-5.75)	(-5.28)	(-2.86)	(-8.92)	(-3.74)	(-7.88)	(-11.28)	(-6.42)	(-14.21)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO	NO	NO
Year × Country FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES
Observations	43,220	43,220	43,220	74,241	74,241	74,241	13,933	13,933	13,933	131,394	131,394	131,394
Adjusted R^2	0.051	0.059	0.029	0.055	0.058	0.001	0.062	0.038	0.043	0.062	0.091	0.053

t statistics in parentheses

the probability to vote for a left-wing populist party by around 25 percent as well.

Finally, columns 10 to 12 pool all countries and regress populist voting behavior on unemployment beliefs. These regressions include country times year fixed effects to account for the country specific political landscape. There is no effect observable on overall populist voting. Nevertheless, a one standard deviation increase in unemployment beliefs decreases the likelihood to vote for a left-wing populist party by 0.6 percentage points and increases the likelihood to vote for a left-wing populist party by 0.65 percentage points. Both coefficients are highly significant at the 1 percent level. Clearly, the negative impact on right-wing populist voting is driven by the Swiss electorate which also dominates the sample observation wise. Apart from unemployment beliefs, individuals with less income are more likely to vote for left-wing and right-wing populist parties. Similarly, more educated and female voters are less likely to vote for right-wing populist parties.

In conclusion, these analyses paint a lot clearer picture than the findings for the size of potential labor income shocks. Across countries, more pessimistic unemployment beliefs significantly increase the probability to vote for a left-wing populist party. This is in line with an interpretation that individuals perceive left-wing populist policies as helpful in reducing labor income risk as soon as a labor income shock materializes. Conversely, there is no positive impact of unemployment beliefs on the likelihood to vote for a right-wing populist party. The findings demonstrate that one needs to be careful when pooling right-wing and left-wing populist parties as the motivation of voting for either might differ significantly.

4.3 Overall Labor Income Risk and Populist Voting

An individual's labor income risk is determined by the size of future income shocks, i.e. the variance of future income, and the probability of these shocks occurring. Intuitively, the size of the labor income shock should only matter if there is a high perceived probability of it occurring. Vice versa, a high perceived probability of labor income shocks should only matter if it is associated with a large negative impact on labor income. Hence, I regress right-wing and left-wing populist voting on the the proxies for task-specific human capital, unemployment beliefs, and the interaction of both.

Table IV.5 shows the results for a regression pooling Germany and Switzerland and including country times year fixed effects. The baseline effects are still similar to the findings in the two preceding sections. On the one hand, task-specific human capital has a positive impact on the likelihood to vote for a right-wing populist party and barely any impact on left-wing populist voting. On the other hand, unemployment beliefs have a significant positive influence to vote for a left-wing populist party whereas there is no clear impact on right-wing populist voting.

However, the interaction between unemployment beliefs and task specificity exhibits a highly interesting pattern. Focusing on columns 1 to 4, the interaction coefficient is significantly negative in three out of four specifications. This means that individuals with highly specific jobs turn away from voting for right-wing populist parties as soon as the probability of a negative labor income shock rises. The results are not necessarily mutually exclusive with the idea that right-wing populist voting is considered as insurance against labor income risk. Intuitively, right-wing parties do not advocate policies that concretely address labor income shocks but lobby for policies that address the electorates fear about diffuse threats to one's income stream that might materialize in the more distant future. Hence, experiencing a rise in the risk of near future labor income induces voters to seek remedies that are concretely insuring them against these disaster shocks like more generous unemployment benefits.

Conversely, columns 5 to 8 indicate the opposite pattern. In three out of four specifications the interaction between the size of the labor income shock and its perceived likelihood increases the probability of voting for a left-wing populist party. This result further supports the argument that left-wing populist voting is perceived as reducing future labor income risk. As the concrete near term labor income risk increases, individuals are significantly more likely to vote for a left-wing populist party. Thus, so far these findings are consistent with individuals voting for populist parties to reduce future labor income risk. However, one has to make the more nuanced argument that voters vote for right-wing populist parties not because of immediate economic insecurity but

Table IV.5: This table shows the results of regressing a populist voting indicator variable as well as right-wing and left-wing populist voting indicator variables on unemployment beliefs, the four proxies for task-specific human capital, and the interaction of both for a pooled sample of German and Swiss individuals. Furthermore, I control for individual characteristics. I estimate OLS regressions with country times year fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Right-wing Populists	Right-wing Populists	Right-wing Populists	Right-wing Populists	Left-wing Populists	Left-wing Populists	Left-wing Populists	Left-wing Populists
Compartmentalization	0.040***				-0.000			
	(9.34)				(-0.01)			
Compartmentalization × Unemployment Beliefs	-0.031***				0.003*			
	(-3.12)				(1.70)			
Occup. unemployment		-0.061				0.048		
		(-0.60)				(0.39)		
Occup. unemployment × Unemployment Beliefs		0.615***				1.528***		
		(2.67)				(4.53)		
Occup. experience			0.008***				-0.002***	
			(6.40)				(-4.58)	
Occup. experience × Unemployment Beliefs			-0.005**				0.002*	
			(-2.49)				(1.73)	
Transition rates				0.059**				0.050***
				(2.11)				(4.18)
Transition rates × Unemployment Beliefs				-0.147***				-0.186***
				(-3.85)				(-6.41)
Unemployment Beliefs	-0.015	-0.049***	0.031*	0.082***	0.018***	0.009***	0.031***	0.181***
	(-1.33)	(-5.67)	(1.76)	(2.91)	(5.63)	(2.88)	(3.01)	(6.82)
Female	-0.051***	-0.066***	-0.025***	-0.065***	-0.003*	-0.004**	-0.005	-0.004**
	(-9.63)	(-12.41)	(-7.00)	(-12.23)	(-1.95)	(-2.24)	(-1.37)	(-2.22)
Age	-0.000	-0.000	-0.000	-0.000	0.000***	0.000***	0.000***	0.000***
	(-1.27)	(-0.98)	(-1.19)	(-0.78)	(3.97)	(3.78)	(2.86)	(4.28)
Education	-0.125***	-0.135***	-0.047***	-0.135***	0.014***	0.014***	0.035***	0.014***
	(-26.40)	(-28.18)	(-14.19)	(-28.08)	(6.98)	(7.45)	(6.90)	(6.90)
Net Income (monthly)	-0.016***	-0.018***	-0.011***	-0.018***	-0.009***	-0.009***	-0.028***	-0.009***
	(-5.14)	(-5.62)	(-3.23)	(-5.54)	(-10.61)	(-10.20)	(-11.93)	(-10.56)
Country × Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	92,977	92,977	30,831	90,534	92,977	92,977	30,831	90,534
Adjusted R^2	0.094	0.086	0.118	0.087	0.039	0.040	0.031	0.041

t statistics in parentheses

rather because of of labor income risk that might materialize in the far future. Yet, this is still consistent with right-wing populist parties protecting domestic workers against the threats of globalization or immigration.

Taking everything into account, my results complement the findings of Pardos-Prado and Xena (2019) and Guiso et al. (2017). On the one hand, I directly link the measures of job specificity of Pardos-Prado and Xena (2019) to populist voting and demonstrate that they mostly affect right-wing populist voting which would be in line with their channel of negative immigration attitudes. On the other hand, I flesh out the proposed role of economic uncertainty on populist voting by Guiso et al. (2017). Rather than unequivocally increasing populist support, it is mostly left-wing populist parties that profit from high perceived job insecurity. Furthermore, my findings might help to explain why parts of the electorate decide to vote for left-wing populists rather than right-wing populists and vice versa. There is evidence that perceived job insecurity moderates the decision of an individual, who experiences high task-specific human capital, whether she turns to a left-wing or right-wing populist party.

4.4 Channels

The previous results suggest that individuals with occupations that would be associated with larger labor income shocks are more likely to vote for right-wing populist parties. There seems to be little evidence that the size of potential labor income disaster shocks affects left-wing populist voting. Conversely, the perceived likelihood of labor income disaster shocks exclusively affects the probability of voting for left-wing populist parties. In this part, I investigate whether individuals indeed perceive populist voting as insurance against labor income shocks.

Right-wing Populist Voting

As argued earlier, there are two channels through which right-wing populist voting could be perceived as reducing future labor income disaster risk. On the one hand, the difficulty of finding another job after experiencing a labor income disaster shock might foster anti-immigration attitudes following the argument of Pardos-Prado and Xena (2019). Hence, individuals with more task-specific human capital might be more inclined to vote for right-wing populist parties as they promise to limit immigration drastically. On the other hand, globalization introduces competition from cheap foreign labor and products. If your job entails a lot of task-specific human capital, you might be more wary of foreign competition as the size of your labor income risk is a lot larger if you lose your job due to foreign competition. Hence, these individuals vote for right-wing populist party that propose isolationist policies.

I explicitly test whether anti-immigration attitudes are the channel through which task-specific human capital strengthens right-wing populist voting. Table IV.6 shows the results of regressing anti-immigration attitudes on the proxies for the perceived difficulty of finding another job. Anti-immigration attitudes are measured as an indicator variable equal to one if an individual expresses strong concerns about immigration.

Columns 1 to 4 display similar findings to table IV.2 for Germany. Both compartmentalization of occupational tasks and occupational unemployment rates have a statistically significant positive effect on immigration attitudes. A one standard deviation increase in the compartmentalization variable increases the likelihood to voice concerns about immigration by 1.7 percentage points compared to an unconditional mean of voicing these attitudes of 28 percent. Conversely, occupational experience has a negative impact on anti-immigration attitudes as well as the likelihood to vote for a right-wing populist party. Finally, occupational permanency has no impact on the dependant variable. As expected, women, higher income, and more educated individuals have a lower probability of having anti-immigration concerns. Interestingly, older individuals tend to hold more negative attitudes towards immigration.

Similarly, columns 5 to 8 also demonstrate similar findings to table IV.3 for Switzerland. Compartmentalization of occupational tasks, occupational unemployment rates, and occupational experience positively affect the probability of holding anti-immigration concerns. For example, a one standard deviation increase in compartmentalization increases the odds of reporting immigration concerns by 1.3 percentage points which is a

Table IV.6: This table shows the results of regressing immigration attitudes on the four proxies of task-specific human capital in Germany, Switzerland, and a pooled sample of both countries. Furthermore, I control for individual characteristics. I estimate OLS regressions with year fixed effects or country times year fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Germany				Switzerland				Full Sample			
	Concern about immigration	Concern about immigration	Concern about immigration	Concern about immigration	Concern about immigration	Concern about immigration	Concern about immigration	Concern about immigration	Concern about immigration	Concern about immigration	Concern about immigration	Concern about immigration
Compartmentalization	0.031***				0.012***				0.016***			
	(10.35)				(6.31)				(10.16)			
Occup. unemployment		1.027***				3.827***				1.250***		
		(12.41)				(9.33)				(15.61)		
Occup. experience			-0.020***				0.003***				-0.008***	
			(-17.67)				(2.68)				(-10.25)	
Transition rates				0.024*				0.025				0.020
				(1.65)				(0.82)				(1.52)
Female	-0.005	-0.020***	-0.024***	-0.017***	0.001	-0.006	-0.009	-0.005	-0.008***	-0.017***	-0.021***	-0.015***
	(-1.16)	(-5.17)	(-6.18)	(-4.34)	(0.12)	(-1.38)	(-0.88)	(-1.13)	(-2.68)	(-5.93)	(-5.76)	(-5.22)
Age	0.002***	0.002***	0.002***	0.002***	0.001***	0.001***	0.001	0.001***	0.001***	0.001***	0.002***	0.001***
	(12.51)	(12.31)	(12.98)	(13.07)	(3.93)	(3.73)	(1.25)	(4.33)	(12.05)	(11.74)	(13.12)	(12.73)
Education	-0.145***	-0.141***	-0.128***	-0.151***	-0.091***	-0.093***	-0.186***	-0.092***	-0.118***	-0.116***	-0.145***	-0.121***
	(-31.22)	(-30.10)	(-26.67)	(-32.60)	(-23.80)	(-24.59)	(-18.68)	(-24.58)	(-39.45)	(-38.88)	(-33.64)	(-40.94)
Net Income (monthly)	-0.048***	-0.043***	-0.038***	-0.049***	-0.014***	-0.013***	-0.029***	-0.014***	-0.027***	-0.025***	-0.041***	-0.027***
	(-14.36)	(-12.97)	(-11.36)	(-14.93)	(-6.68)	(-6.01)	(-5.29)	(-6.57)	(-15.13)	(-14.18)	(-14.81)	(-15.36)
Unemployed	0.055***	0.036***	0.040***	0.053***	0.019	0.012	0.021	0.013	0.064***	0.041***	0.049***	0.063***
	(4.90)	(3.17)	(3.53)	(4.73)	(1.02)	(0.66)	(0.38)	(0.67)	(6.41)	(4.12)	(4.41)	(6.27)
Observations	132,927	132,927	132,927	132,893	108,578	108,578	17,705	104,351	241,505	241,505	150,632	237,244
Adjusted R^2	0.040	0.041	0.043	0.039	0.145	0.145	0.031	0.147	0.092	0.093	0.039	0.091

t statistics in parentheses

10 percent increase compared to the unconditional probability of 13 percent. Like in the other analyses, occupational permanency has no impact on the outcome variable. Overall, these findings suggest that the size of potential labor income disaster shocks indeed has an impact on anti-immigration attitudes. Individuals with more task-specific human capital report more hostile attitudes towards immigration.

Obviously, these results raise the question whether immigration attitudes fully mediate the relationship between task-specific human capital and right-wing populist voting. In other words, can immigration attitudes fully explain how an individual's size of potential labor income shocks induces right-wing populist voting. To test this relationship, I employ the methodology of Baron and Kenny (1986) and regress right-wing voting on compartmentalization of occupational tasks and occupational unemployment as well as immigration attitudes for Germany and Switzerland. If the impact of the proxies for task-specific human capital is diminished or vanishes, this suggests partial or complete mediation through immigration attitudes. I conduct this analysis only for compartmentalization and occupational unemployment as these variables have the most consistent impact on right-wing populist voting behavior. Table IV.7 shows the results of this analysis.

Clearly, there is little evidence for mediation. Columns 1 and 3 demonstrate that the influence of compartmentalization of occupational tasks is barely reduced by around 20 percent and 10 percent in Germany and Switzerland, respectively. Conversely, the impact of occupational unemployment on right-wing populist voting becomes insignificant after including immigration attitudes in Germany and it is reduced by 16 percent in Switzerland. Hence, hostile immigration attitudes do not appear to explain the impact of the size of labor income shocks on right-wing populist voting. Nevertheless, concerns about immigration are the most important driver of right-wing populist voting. Voicing concerns about immigration increases the likelihood to vote for the *AfD* in Germany by 3.1 percentage points whereas a one standard deviation increase in the compartmentalization variable increases the same probability by only 0.23 percentage points. Similarly, concerns about immigration raise the likelihood to vote for the *SVP* in Switzerland by

Table IV.7: This table shows the results of regressing a right-wing voting indicator variable on immigration attitudes, compartmentalization of occupational tasks, and occupational unemployment. Furthermore, I control for individual characteristics. I estimate OLS regressions with either year or year times country fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Right-wing Populists					
	Germany		Switzerland		Full Sample	
Concern about immigration	0.031***	0.032***	0.250***	0.253***	0.126***	0.130***
	(17.48)	(17.60)	(30.66)	(30.93)	(31.36)	(32.07)
Compartm.	0.004***		0.031***		0.030***	
	(3.61)		(7.87)		(9.09)	
Occup. unempl.		0.024		7.933***		-0.367***
		(0.68)		(8.95)		(-7.08)
Female	-0.006***	-0.007***	-0.066***	-0.079***	-0.035***	-0.046***
	(-5.85)	(-7.29)	(-9.80)	(-11.88)	(-9.04)	(-12.04)
Age	-0.000	-0.000	-0.001**	-0.001**	-0.000	-0.000
	(-1.21)	(-0.96)	(-2.07)	(-2.24)	(-1.52)	(-1.00)
Education	-0.004***	-0.005***	-0.140***	-0.146***	-0.080***	-0.088***
	(-4.76)	(-5.09)	(-24.00)	(-25.14)	(-22.53)	(-24.60)
Net Income	-0.002**	-0.002**	-0.014***	-0.012***	-0.011***	-0.012***
	(-2.11)	(-2.27)	(-4.08)	(-3.35)	(-4.15)	(-4.82)
Unemployed	0.001	-0.000	0.010	-0.000	-0.009	-0.004
	(0.13)	(-0.03)	(0.36)	(-0.01)	(-1.05)	(-0.49)
Year FE	YES	YES	YES	YES	NO	NO
Year × Country FE	NO	NO	NO	NO	YES	YES
Observations	52,742	52,742	70,416	70,416	123,158	123,158
Adjusted R^2	0.058	0.058	0.110	0.106	0.136	0.129

t statistics in parentheses

25 percentage points whereas a one standard deviation increase in the compartmentalization variable only increases this probability by 0.34 percentage points. Even though these magnitudes are not directly comparable, it becomes clear that anti-immigration attitudes drive right-wing populist voting.

The alternative explanation for the rise in right-wing populist voting proposed in the finance and economics literature argues that globalization has lead to economic winners and losers. The losers of globalization are inequality averse and vote for right-wing populist parties because they promise to limit foreign economic competition and to protect domestic jobs (Pástor & Veronesi, 2021). I use the china import shock of Colantone and Stanig (2018) as measure of foreign competition. This variable is measured as the change in imports from china in a given region normalized by the region's workers and weighted by the importance of this industry. The import shock is measured on a NUTS-2 region level. I interact this measure with the proxies for task-specific human capital to test whether individuals that are exposed to larger potential labor income disaster risk and then are exposed to globalization via foreign imports are more likely to vote for more right-wing populist parties. Unfortunately, I can only conduct this analysis for Switzerland as the measure of import shocks is only available for the early 2000s. At this time, the *AfD* was not yet existent in Germany. Table IV.8 shows the results of this analysis.

Columns 1 to 4 demonstrate that in line with the argument of Colantone and Stanig (2018), regions that are more exposed to Chinese imports are more likely to vote for a right-wing populist party in Switzerland. For example in column 1, a one standard deviation increase in foreign exports increases the likelihood of a right-wing populist vote by 1.4 percentage points. Similar to earlier results, task-specific human capital still has a statistically significant positive impact on the likelihood of voting for a right-wing populist party. Nevertheless, the interaction between import shocks and task-specific human capital has no statistically significant positive impact on right-wing populist voting. Even more, in column 4 there appears to be a significant negative relationship between import shocks and transition rates, and the probability of voting for a right-wing populist party. Overall, there is no evidence that task-specific human capital affects right-wing populist voting through the channel of fear of foreign competition. If increasing globalization was a concern for domestic workers' labor income risk, one would expect a more pronounced positive reaction to import shocks if a voter has a lot of task-specific human capital.

Furthermore, building on the argument of (Pástor & Veronesi, 2021) inequality aversion plays a crucial role in determining an individual's reaction to globalization shocks. According to their model, individuals observe the increasing inequality in society and

Table IV.8: This table shows the results of regressing a right-wing populist voting indicator variable on the import shock by Colantone and Stanig (2018), the four proxies for task-specific human capital and the pairwise interaction with the import shock variable. Furthermore, I control for individual characteristics. I run this analysis for the SHP and I estimate OLS regressions with year fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Right-wing Populists	Right-wing Populists	Right-wing Populists	Right-wing Populists
Import shock	0.716**	0.660**	2.172**	6.488**
	(2.21)	(2.19)	(2.29)	(2.43)
Compartmentalization	0.023**			
	(2.33)			
Import shock × Compartmentalization	0.152			
	(0.58)			
Occup. unemployment		6.371***		
		(3.22)		
Import shock × Occup. unemployment		53.787		
		(0.95)		
Occupational experience			0.010***	
			(3.34)	
Import shock × Occupational experience			-0.132	
			(-1.04)	
Transition rates				0.217**
				(1.96)
Import shock × Transition rates				-6.137**
				(-2.10)
Female	-0.076***	-0.089***	-0.079***	-0.089***
	(-8.26)	(-9.64)	(-6.66)	(-9.34)
Age	-0.000	-0.000	-0.001	-0.000
	(-0.66)	(-0.80)	(-1.35)	(-0.36)
Education	-0.149***	-0.154***	-0.150***	-0.157***
	(-18.51)	(-19.11)	(-15.07)	(-19.01)
Net Income (monthly)	-0.027***	-0.024***	-0.019***	-0.029***
	(-5.77)	(-5.19)	(-2.85)	(-5.90)
Unemployed	-0.039	-0.048	0.010	-0.034
	(-1.28)	(-1.55)	(0.14)	(-1.07)
Year FE	YES	YES	YES	YES
Observations	45,786	45,786	9,913	43,336
Adjusted R^2	0.059	0.057	0.046	0.055

t statistics in parentheses

punish the benefiting elites by voting for right-wing populist parties that promise to limit globalization. Hence, the necessary condition for a backlash against globalization based explanation of right-wing populist voting is that more inequality averse individuals are more likely to vote for right-wing populist parties. In table IV.9, I regress right-wing populist voting on inequality aversion to test this hypothesis.

Table IV.9: This table shows the results of regressing the right-wing or left-wing populist voting indicator variable on inequality aversion in Germany, Netherlands, and Switzerland. Furthermore, I control for individual characteristics. I estimate OLS regressions with year fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Germany		Netherlands		Switzerland	
	Right-wing Populists	Left-wing Populists	Right-wing Populists	Left-wing Populists	Right-wing Populists	Left-wing Populists
Inequality Aversion	0.001	0.004	-0.020**	0.019*	-0.066***	0.006***
	(1.00)	(1.06)	(-2.01)	(1.72)	(-10.89)	(7.65)
Female	-0.003	0.004	-0.044**	-0.011	-0.059***	-0.001
	(-1.00)	(0.23)	(-2.53)	(-0.57)	(-9.62)	(-1.14)
Age	-0.000	-0.000	-0.002***	-0.001***	0.000	-0.000
	(-0.99)	(-0.04)	(-3.99)	(-2.73)	(0.69)	(-0.86)
Education	.	.	-0.088***	-0.014	-0.170***	0.006***
			(-3.89)	(-0.48)	(-31.38)	(3.28)
Income (monthly)	-0.002	-0.018	-0.045***	-0.111***	-0.007***	-0.001**
	(-0.99)	(-1.36)	(-2.74)	(-5.38)	(-2.80)	(-2.53)
Unemployed	0.005	-0.023	0.022	0.058	0.005	0.005
	(1.00)	(-1.38)	(0.34)	(0.83)	(0.33)	(1.49)
Year FE	NO	NO	NO	NO	YES	YES
Observations	564	564	1,362	1,362	101,782	101,782
Adj. R^2	0.001	0.001	0.024	0.028	0.045	0.002

t statistics in parentheses

Unfortunately, for Germany and the Netherlands a question related to inequality aversion has been only asked in one wave. Columns 1 and 2 show no statistically significant relationship between inequality aversion and right-wing populist voting. However, it is not clear whether this is due to the very limited sample size. Nevertheless, columns 3 and

4 display a much clearer picture for the Netherlands. Inequality averse individuals are actually *less* likely to vote for a right-wing populist party whereas they are *more* likely to vote for a left-wing populist party. A one step increase in inequality aversion decreases the probability to vote for a right-wing populist party by 2 percentage points which is statistically significant at the 5 percent level. Conversely, it increases the likelihood of a left-wing populist vote by the same magnitude.

Due to data availability, I employ a different proxy for inequality aversion in Switzerland which is available in all waves. Individuals are asked whether they favor higher taxation for high income earners. I argue this is a good proxy for inequality aversion as the most salient policy that is proposed to curb wealth inequality is high taxes for high income earners (Piketty, 2014). Columns 5 and 6 demonstrate similar results for Switzerland compared to the Netherlands. Again, inequality aversion has a statistically significant negative impact on right-wing populist voting and a positive impact on left-wing populist voting. Individuals that favor higher taxes for high income brackets are 6.6 percentage points less likely to vote for the *SVP*. Overall, there is no evidence that inequality averse households vote for right-wing populist parties which favor isolationist policies and economic nationalism. Contrarily, they are more likely to vote for left-wing populist parties which promise redistributive policies to curb inequality. This does not come as too much of a surprise as left-wing populist parties denounce wealth inequality for decades and propose policies that are targeted at aggressively changing the economic status quo.

In conclusion, task-specific human capital neither affects right-wing populist voting through the channel of anti-immigration attitudes nor through the channel of a backlash against globalization. These were the two explanations for the surge of right-wing populist parties proposed in the economics and finance literature. Clearly the four measures of task-specific human capital are correlated with right-wing populist voting. However, after my analyses it remains unclear why they would predict right-wing populist voting. More research is needed to identify the relevant channel. Potentially, they are simply correlated with an unobserved characteristic that drives voting behavior.

Left-wing Populist Voting

As outlined earlier, the potential motive through which pessimistic unemployment beliefs could increase the likelihood of left-wing populist voting is the desire to insure oneself against labor income shocks. Left-wing populist parties typically emphasize inequality in society and advocate for the expansion of the welfare state and redistributive policies. There are two subgroups of the population that should be particularly inclined to insure against labor income shocks. The first group are households that are financially fragile which means that they have little wealth to smooth consumption if labor income shocks hit. The second group are households that do not save from one period to the next which means that there level of precautionary savings is either stagnating or decreasing. If one motif for voting for left-wing populist parties is to insure against potential labor income shocks, one would expect that these aforementioned groups are especially likely to vote for a left-wing populist party as the perceived probability of labor income shocks rises. Hence, in table IV.10 I regress left-wing populist voting on unemployment beliefs, a proxy for the financially fragile groups and the interaction of both.

Across specifications, more pessimistic unemployment beliefs increase the likelihood to vote for a left-wing populist party. Being a financially fragile household meaning a very low level of precautionary savings also appears to positively influence the likelihood of voting for a left-wing party, even though this effect is only statistically significant in Germany. Financially fragile households are 2.7 percentage points more likely to vote for a left-wing populist party. Interestingly, The interaction between low levels of precautionary savings and unemployment beliefs is statistically significant negative in Germany and there is no effect in the other countries observable. This negative coefficient contradicts the idea that individuals vote for left-wing populist parties to insure against labor income shocks as financially fragile households should be more willing to vote for left-wing populist if the subjective probability of these labor income shocks rises.

Conversely, households that have a strictly positive saving rate are less likely to vote for populist parties across the three countries. This is not surprising as these households tend to be wealthier and benefit less form redistributive policies. For example, households

Table IV.10: This table shows the results of regressing the right-wing or left-wing populist voting indicator variable on unemployment beliefs, financial fragility, an indicator variable equal to one if a household saves, and the pairwise interaction between the three variables in Germany, Netherlands, and Switzerland. Furthermore, I control for individual characteristics. I estimate OLS regressions with year fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the $p < 10\%$, $p < 5\%$, and $p < 1\%$ levels, respectively.

	Germany		Switzerland		Netherlands	
	Left-wing Populists	Left-wing Populists	Left-wing Populists	Left-wing Populists	Left-wing Populists	Left-wing Populists
Unemp. Beliefs	0.054***	0.044***	0.004*	0.008*	0.076***	0.089***
	(6.98)	(3.99)	(1.91)	(1.73)	(4.95)	(3.54)
Financial Fragility	0.027***		0.004		0.035	
	(5.39)		(1.56)		(1.42)	
Fin. Frag. × Unemp. Bel.	-0.031**		0.003		-0.016	
	(-2.06)		(0.46)		(-0.24)	
HH saves		-0.007*		-0.003**		-0.018*
		(-1.72)		(-2.04)		(-1.84)
HH saves × Unemp. Bel.		0.011		-0.007		-0.030
		(0.83)		(-1.39)		(-1.05)
Female	0.003	0.004	-0.001	-0.001	0.017*	0.016*
	(0.89)	(1.14)	(-0.66)	(-0.64)	(1.84)	(1.78)
Age	0.000	0.000	0.000	0.000	0.002***	0.002***
	(0.27)	(0.43)	(0.51)	(0.26)	(4.63)	(4.42)
Education	0.049***	0.053***	0.005***	0.005***	-0.033***	-0.032***
	(8.71)	(9.24)	(3.41)	(3.44)	(-3.00)	(-2.94)
Income (monthly)	-0.050***	-0.052***	-0.002***	-0.001**	-0.077***	-0.072***
	(-13.30)	(-14.04)	(-2.70)	(-2.41)	(-7.76)	(-7.18)
Year FE	YES	YES	YES	YES	YES	YES
Observations	35,344	43,058	74,074	73,627	13,880	13,933
Adjusted R^2	0.031	0.029	0.002	0.002	0.043	0.044

t statistics in parentheses

reporting a positive saving rate are 1.8 percentage points less likely to vote for a left-wing populist party in the Netherlands. Yet, the interaction between unemployment beliefs and the saving behavior of households is insignificant across countries. Again, these findings do not support the hypothesis that individuals vote for populist parties to insure against labor income shocks.

Next, more risk averse individuals should be more willing to insure against labor income shocks than less risk averse individuals if the labor income risk increases. In the context of left-wing populist voting this means that more risk-averse households should be more inclined to vote for a left-wing populist party if they have high perceived labor income risk. Hence, in table IV.11 I regress left-wing and right-wing populist voting on unemployment beliefs, risk aversion and the interaction of both.

Table IV.11: This table shows the results of regressing left-wing and right-wing populist voting on unemployment beliefs, risk aversion, and the interaction of both. Furthermore, I control for individual characteristics. Columns 1 and 2 show the results for Germany and columns 3 and 4 for Switzerland. I estimate OLS regressions with year fixed effects. Standard errors are clustered by individual, and *, **, and *** denote statistical significance at the p < 10%, p < 5%, and p < 1% levels, respectively.

	Germany		Switzerland	
	Left-wing Populists	Right-wing Populists	Left-wing Populists	Right-wing Populists
Unemployment Beliefs	0.004	-0.007	0.004	-0.077***
	(0.22)	(-0.77)	(0.62)	(-3.23)
Risk Aversion	-0.001	-0.001	-0.001***	0.006***
	(-1.35)	(-1.30)	(-2.75)	(2.79)
Unemployment Beliefs × Risk Aversion	0.010***	0.001	0.000	0.004
	(2.92)	(0.60)	(0.12)	(0.83)
Female	0.001	-0.014***	-0.001	-0.090***
	(0.13)	(-7.85)	(-0.52)	(-11.82)
Age	0.000	0.000	0.000	-0.000
	(0.33)	(0.46)	(0.81)	(-1.36)
Education	0.046***	-0.017***	0.004***	-0.173***
	(7.65)	(-9.99)	(2.70)	(-26.58)
Net Income (monthly)	-0.060***	-0.011***	-0.002***	-0.018***
	(-14.18)	(-6.69)	(-2.59)	(-4.59)
Year FE	YES	YES	YES	YES
Observations	28,878	28,878	63,406	63,406
Adjusted R^2	0.027	0.054	0.002	0.062

t statistics in parentheses

On the one hand, columns 1 and 3 demonstrate the impact of risk aversion on left-wing populist voting in Germany and Switzerland. Interestingly, the positive impact of unemployment beliefs vanishes when controlling for risk aversion. At the same time, more risk-averse individuals are, on average, less likely to vote for left-wing populist parties. Yet, quantitatively this effect is rather small. Interestingly, column 1 reveals that the interaction between risk aversion and unemployment beliefs has a highly significant positive effect on the probability to vote for a left-wing populist party. This is in line with the hypothesis that more risk averse individuals should be more inclined to insure against labor income shocks if the perceived probability of these shocks increases. Yet, even though the same coefficient is positive for the Swiss sample, it is close to zero and not statistically significant. It is not clear whether this is due to a lack of effect or due to the limited size of the Swiss left-wing populist voter sample.

On the other hand, columns 2 and 4 show that unemployment beliefs again have a negative impact on the likelihood to vote for a right-wing populist party. Simultaneously, the effect of risk aversion on right-wing populist voting is negative for Germany and significantly positive for Switzerland suggesting institutional differences. Finally, the interaction of risk aversion and unemployment beliefs has no influence on the likelihood to vote for a right-wing populist party. This finding reinforces that voters do not perceive right-wing populist voting as insurance against imminent labor income risk. Overall, this analysis provides some evidence that voters might perceive voting for a left-wing populist party as reducing their perceived labor income risk. Nevertheless, this evidence is very limited. Right-wing populist voters clearly do not consider economic motives in their voting decision.

In conclusion, there is little evidence that individuals vote for populist parties to insure against future labor income shocks. On the one hand, task-specific human capital does not affect right-wing populist voting through the channels of immigration attitudes or a backlash against globalization. Therefore, it is unclear why the size of labor income shocks is correlated with right-wing populist voting. On the other hand, there is little evidence that individuals that are vulnerable against labor income shocks are more likely to vote for left-wing populist parties as the perceived probability of these income shocks increases. This suggests that labor income risk is not the primary concern when voting for a left-wing populist party. Hence, it is unlikely that individuals vote for right-wing or left-wing populist parties to reduce their perceived future labor income risk.

5 Conclusion

Populist parties have experienced a renaissance in the aftermath of the financial crisis and the subsequent refugee crisis. The importance of this trend for the political discourse and subsequent policy making is undisputed. Yet, the reasons for the success of these parties remain not well understood. The academic literature in economics and finance has focused on theories of economic uncertainty, job displacement due to globalization, and domestic labor competition through immigration. Yet, all of these explanations are rooted in a voter's concern about future labor income risk.

In this paper, I test the hypothesis that populist voting is a tool for households to reduce their perceived labor income risk. Indeed, I find that individuals that would experience larger labor income shocks in case of unemployment are more likely to vote for right-wing populist parties. Conversely, individuals that have a higher perceived probability of unemployment are more likely to vote for left-wing populist parties. Interestingly, my results suggest that the central piece that determines the choice whether to vote for a right-wing or left-wing party is the likelihood of these labor income shocks. If a person is certain she loses her job, she votes for a left-wing populist party which promises more support in case of unemployment. On the contrary, if she feels that the high task-specific human capital insulates her against unemployment, she will vote for a right-wing populist party that promises to insulate her further by keeping non-domestic competition out.

Furthermore, I explore further whether individuals perceive populist voting as reducing future labor risk. However, I do not find any evidence that voters perceive right-wing populist parties as reducing their future labor income risk through either limiting immigration or isolationist economic policies. Similarly, there is little evidence that more financially fragile or risk averse individuals are more likely to vote for left-wing populist parties that promise to reduce the size of labor income shocks.

The causal inferences that can be drawn from this study are limited due to the rigid nature of voting behavior. Including person fixed effects would have improved identification considerably. Furthermore, this study does not exploit any exogenous shocks, which would have been an alternative way to mitigate reverse causality concerns associated with job selection or party affiliation. In conclusion, I provide evidence that task-specific human capital and unemployment beliefs play an important role in the decision to vote for a populist party. Furthermore, to my knowledge I am the first to flesh out the role of beliefs about future labor income in the decision whether to vote for a right-wing or left-wing populist party. However, I find little support for the idea that populist voting is considered to limit labor income risk.

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A Variable Description

Concept	Question
Germany	
Concern about Immigration	How concerned are you about the following issues? - Immigration to Germany *1 - Very concerned* *2 - Somewhat concerned* *3 - Not concerned at all*
Unemployment Beliefs	How likely is it that you will experience the following career changes within the next two years? - Will you lose your job? *0 - This will definitely not happen* ... *10 - This will definitely happen*
Financial Fragility	The household has financial reserves for emergencies. *0 - Yes* *1 - No*
HH does save	Do you usually have money left over at the end of the month that you can put aside for larger purchases, emergencies, or to build savings? *1 - Yes, precautionary savings*
Inequality Aversion	A society is fair when income and wealth are equally distributed among all people. *1 - Agree strongly* ... *5 - Disagree strongly*
Risk Aversion	In general, are you someone who is willing to take risks or do you try to avoid risks? *0 - Risk averse* ... *10 - Fully willing to take risks*
Netherlands	
Concern about Immigration	There are too many people of foreign origin or descent in the Netherlands. *1 - Fully disagree* ... *5 - Fully agree*
Unemployment Beliefs	Do you think that there is any chance that you might lose your job in the coming year? *0 percent - 100 percent*

Financial Fragility	Were you in arrears on one or more bills within the last year? *1 - Yes* *0 - No*
HH does save	How would you describe the financial situation of your household at this moment? *1 - We are accumulating debt* … *5 - we have a lot of money to spare*
Switzerland	
Concern about Immigration	Are you in favour of Switzerland offering foreigners the same opportunities as those offered to Swiss citizens, or in favour of Switzerland offering Swiss citizens better opportunities? *1 - In favour of equality of opportunities* *2 - Neither* *3 - In favour of better opportunities for Swiss citizens*
Unemployment Beliefs	How do you evaluate the risk of becoming personally unemployed in the next 12 months? *0 - No risk at all* … *10 - A real risk*
Financial Fragility	Arrears of payments of HH bills: Last 12 months *1 - Yes* *0 - No*
HH does save	Income: assessment of income and expenses *1 - your household gets into debt* … *4 - your household can save money*
Inequality Aversion	Are you in favour of an increase or in favour of a decrease of the tax on high incomes? *1 - In favour of an increase* *2 - Neither* *3 - In favour of a decrease*
Risk Aversion	Are you generally a person who is fully prepared to take risk or do you try to avoid taking risks? *0 - Avoid taking risk* … *10 - Fully prepared to take risk*

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WORKING PAPERS

Mortality Beliefs and Saving Decisions: The Role of Personal Experiences

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.

Distorted Unemployment Beliefs and Stock Market Participation

I find that households severely overestimate their future unemployment probability. I argue that this distorted perception of labor income risk significantly reduces households' stock investments. In reduced form regressions, I demonstrate that these unemployment expectations are highly predictive of actual unemployment shocks and significantly reduce households' risky share. Building on that, I structurally estimate a life-cycle model of portfolio choice that incorporates the empirical distortion in unemployment expectations. The model matches the evolution of wealth, equity share and participation rates with more plausible risk aversion estimates than the conventional model. I find that distorted unemployment expectations can explain low stock market investment rates especially among young and less wealthy households.

CONFERENCES

2023: European Finance Association (EFA), European Economic Association (EEA-ESEM, scheduled), American Economic Association (poster session), Swiss Finance Society (SGF)

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