# Distorted Unemployment Beliefs and Stock Market Participation

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February 28, 2023

**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 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.

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# 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. Low stock market participation rates are problematic as households potentially forego large lifetime utility gains. I establish the pervasive fact that individuals hold on average highly distorted, namely too pessimistic, unemployment beliefs. I argue that this 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 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 risk-free asset to reasonably maintain their level of consumption in the next period if the unemployment shock materializes.

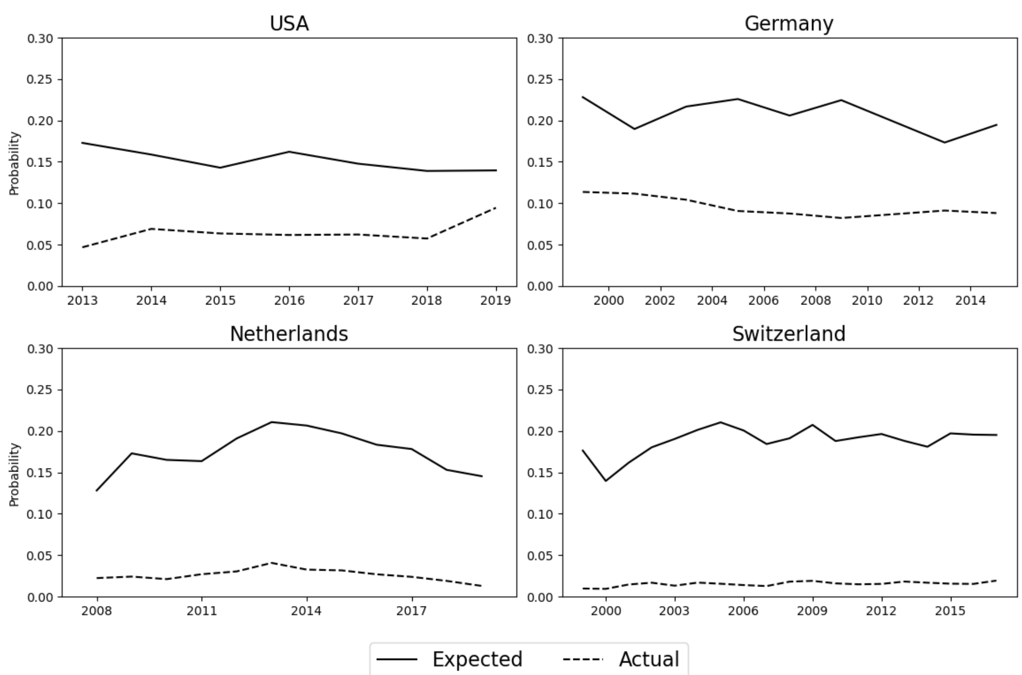


**Figure 1:** Unemployment expectations versus actual unemployment outcomes.

Figure 1 summarizes the main empirical finding of this paper. 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 a time span of over 20 years. Augmenting the classic life-cycle model of portfolio choice by distorted unemployment beliefs reduces households' investment in the risky asset considerably. Structural estimations reveal that including distorted beliefs into the model severely improves the model fit compared to the baseline model. Hence, I argue in this paper that distortions in perceived labor income disaster risk can help to explain low stock market participation rates.

In this paper, I establish three facts concerning elicited unemployment expectations. 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 expectations do correspond to the objective probabilities. Focusing on the results for the USA, the subjective job loss likelihood decreases monotonically across income quintiles which is in line with the actual probabilities. Similarly, female participants report slightly higher unemployment expectations than males which again is in line with actual outcomes.

Second, unemployment expectations are highly persistent both at an aggregate level as well as within person. On an aggregate level, Figure 1 demonstrates that average unemployment expectations 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 expectations from one period to the next reveals that most individuals correctly report a 0 to 10 percent job loss likelihood. 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 increases at the extensive margin the probability of actually losing in individual's job by 4.9 percentage points in the USA, 8 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 expectations are even within-person highly predictive of future outcomes.

On top of that, I supplement these theoretical findings by running reduced form regressions that demonstrate that an increase in unemployment expectations leads to a within person decrease in the risky share. On average, an one standard deviation increase in unemployment expectations reduces the risky share by 0.6 percentage points and the conditional risky share by 1.4 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 actually consider unemployment expectations in their financial decision making.

Overall, I find that the discrepancy of subjective and actual unemployment expectations is highly stable and subjective unemployment expectations are predictive of investment in the risky share. Hence, I explore the implications of this novel finding for the standard theoretical model of stock market participation. I augment a life-cycle model of consumption and saving in a risky and risk-free asset by the distorted unemployment expectations. Next, I structurally estimate the unobserved parameters like relative risk aversion, discount factor, and participation cost. Hereby, I target the evolution of wealth, stock market participation, and risky share over an agent's life-cycle as observed in the Survey of Consumer Finances (SCF). I find that including unemployment expectations calibrated to survey responses leads to significantly more plausible parameter combinations that optimally fit the model moments to the observed empirical moments. In the baseline model, the structural estimation reveals a coefficient of relative risk aversion of 16.955, a discount factor of 0.634, and a per period fixed participation cost of 1.1 percent. Conversely, incorporating distorted expectations reduces the risk aversion to 10.475 and increases the discount factor to 0.720 and the participation cost to 2.4 percent. This vast reduction in required risk aversion is remarkable considering that only the the expectations of the agents are changed. Agents still face the objective probability of losing their job. Hence, the likelihood of experiencing this disaster labor income shock is relatively low.

In the final part of the paper, I explore further how distorted unemployment expectations 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. Introducing a disaster labor income shock significantly reduces the investment in the risky share at low to intermediate levels of wealth. Hence, the policy function becomes nearly upward sloping which is in line with the empirical fact that more wealthy individuals invest more into the risky asset than less affluent individuals. Furthermore, this contrasts with conventional policy functions for models without an income disaster shock. In the baseline case, agents with low to intermediate levels of wealth are supposed to invest 100 percent of their wealth into the risky asset and only as wealth further rises the risky share declines. Moreover, unemployment expectations have a persistent negative effect on the risky share of younger households. This pronounced effect helps to explain the low stock market participation rates and low risky share for younger individuals. On the one hand, younger individuals tend to be less wealthy and thereby are more vulnerable to large labor income shocks. Hence, they have a stronger precautionary savings motive and invest less into the risky asset. On the other hand, even at higher levels of wealth they invest less into the risky asset when facing distorted perceived unemployment probabilities.

My paper mainly relates to two strands of the finance literature. First of all, I contribute to the scarce literature in finance on unemployment expectations. There are only a few papers that look explicitly at the unemployment expectations elicited in surveys. Notably, Dickerson and Green (2012) and Kuchler and Zafar (2019) find that unemployment expectations are highly predictive of actual job loss. This is in line with my results for a significantly broader set of countries. On top of that, Stephens Jr (2004) and Pettinicchi and Vellekoop (2019) link elicited unemployment expectations 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 expectations 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.

Hence, I closely relate to the literature in finance 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, Gomes, and Maenhout (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 (2021) 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 household's financial decision making. Hence, households actually consider these expectations when taking decisions related to portfolio choice. On top of that, I only change an agent's expectations not the actual outcomes. There little research so far that has considered subjective expectations 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 expectations in four large household panels around the world. I present descriptive statistics and link unemployment expectations 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 (2021) for labor income growth.

## 2 Unemployment Expectations in the Data

### 2.1 Data

In this section, I describe the micro data on unemployment expectations. The data on unemployment, unemployment expectations, and demographics come from four large hosuehold 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 expectations. Each respondent stays in the panel for 12 months before she is rotated out of the survey. Second, for the German data I utilize the German Socio-Economic Panel (GSOEP). 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 panels aims to survey a nationally representative sample of adults typically starting at the age of 16.

[Insert Table 1 about here.]

Table 1 shows the descriptive statistics for each of the four panels. As each of these surveys aims to cover a representative sample of the respective population, roughly half of the sample is female and the average age lies around 50. The net income of households differs significantly across countries both due to differing levels of consumer prices as well as currencies. On top of that, 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. However, unemployment rates differ significantly from country to country ranging from a little over 1 percent in Switzerland to around 9 percent in the USA. 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 expectations 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 C.

Furthermore, I utilize the employment status of individuals to compare it directly to their unemployment expectations. 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. 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 expectations and establish several empirical patterns that persist across countries and time with respect to these unemployment expectations.

## 2.2 Average Unemployment Expectations

In this part, I further explore the large discrepancy between perceived unemployment expectations and the actual job loss probabilitx. Table 2 shows the average unemployment expectations and actual unemployment probability for the SCE, GSOEP, LISS, and SHP surveys. One the one hand, the perceived probability of becoming unemployed does not vary much across countries. It ranges from, on average, 15 percent in the US and 20 percent in Germany. However, in the GSOEP individuals are asked about the probability of losing one's job within *2 years* opposed to *1 year* in the other panels. On the other hand, 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 expectations 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.

[Insert Table 2 about here.]

Comparing reported unemployment expectations and the actual probability of job loss reveals that across countries reported unemployment expectations are a lot larger than the actual probability of losing one's job. Focusing on the USA, the perceived probability of 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 expectations 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 expectations from the micro data. Participants consistently overestimate the likelihood of job loss. This suggests that individuals hold distorted unemployment expectations. 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 expectations are distributed. Figure 2 plots the distribution of subjective unemployment expectations 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, this further suggests that these reported probabilities contain information about participants' expectations.

[Insert Figure 2 about here.]

Table 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 expectations, 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 expectations 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 expectations. 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 expectations and the actual outcomes. However, cross-sectional sample splits show that across individuals the dispersion in unemployment expectations 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 expectations are also meaningful in the time-series. Fortunately, the panel structure of the surveys allows me to test the persistence of expectations and whether unemployment expectations are predictive of actual unemployment.

## 2.3 Persistence of Unemployment Expectations

In this section, I explore the persistence of unemployment expectations over time. Figure 1 shows that on an aggregate level expectations do not vary significantly. For example, in the USA average unemployment expectations 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 expectations 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 expectations on an individual level. Table 4 shows a transition matrix for bins of unemployment expectations 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.

[Insert Table 4 about here.]

However, unemployment expectations tend to consistently revert back to low levels even after individuals report unemployment expectations of over 80 percent. For example, 54 percent of individuals in the Netherlands that reported unemployment expectations of above 80 percent state unemployment expectations 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.

[Insert Table 3 about here.]

I confirm the results of the transition matrix in a regression context. Table 3 shows the results of regressing this year's unemployment expectations on unemployment expectation 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 expectations increases, on average, today's unemployment expectations 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 expectations are highly predictive of future unemployment expectations. Overall, if the rare jumps to high unemployment expectations reveal private information, they should translate into actual unemployment. Hence, in the next section I test this hypothesis.

### 2.4 Unemployment Expectations and Actual Unemployment

Next, I test whether unemployment expectations 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 5 displays the results of the analysis.

[Insert Table 5 about here.]

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

### 2.5 Unemployment Expectations and Risky Share

Finally, I tackle the question whether these unemployment expectations actually translate in changes in financial decision-making. I argue in this paper that unemployment expectations 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 expectations 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 expectations 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.

[Insert Table 6 about here.]

Table 6 shows the results of regressing the risky share, conditional risky share, and the participation rate on unemployment expectations while controlling for actual unemployment. In the first two columns, I regress the risky share on standardized subjective unemployment expectations both with and without person fixed effects. On average, a one standard deviation increase in perceived job loss risk decreases the risky share by 0.6 percentage points both with and without person fixed effects. This coefficient statistically significant at the 5 and 1 percent level, respectively. This change of 0.6 percentage points is sizable considering the average risky share in the sample is only 8.3 percent.

Similarly, an one standard deviation increase in perceived unemployment expectations reduces the conditional risky share by 1.4 percentage points without person fixed effects and by 0.8 percentage points after including fixed effects. This effect is statistically significant at the 5 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 expectations. 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 expectations 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 expectations 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 expectations 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 expectations elicited in surveys reflect actual expectations 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 expectations. The micro data on unemployment expectations reveals three robust patterns which I summarize in this section. First, individuals persistently overestimate the likelihood of losing their job in the future. This 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 expectations are persistent over time. This is the case both on the aggregate level and within individual. On the aggregate level this shows that the large distortion of expectations is not an outlier. On the individual level the persistence of unemployment expectations 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 expectations are highly predictive of future actual unemployment both at the extensive and intensive margin. This indicates that participants convey private information about future employment outcomes through these probabilities. Again, this is further evidence that elicited unemployment expectations can be useful for researchers.

Furthermore, I find that changes in subjective unemployment expectations 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 expectations, therefore, decreases risky asset holding. Overall, these findings suggest that unemployment expectations 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 expectations 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. Investor $i$'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 $\gamma$ 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, $\nu_{it}$ represents persistent income shocks, and $\epsilon_{it}$ idiosyncratic, temporary shocks to income. The persistent income shocks are modeled as:

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

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

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

where $\overline{f_t}$ represents a function of the life-cycle trajectory of income common to all workers. Conversely, $\alpha_i$ is individual specific and assumed to be normally distributed with standard deviation $\sigma_\alpha$. Hence, $\alpha_i$ represents the initial dispersion in incomes of workers.

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:

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

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 $\omega_t$ and consequently receive a transitory income shock of $\kappa$. 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 expectations about the likelihood of losing their job. Hence, agents hold the following expectations 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 $\mu_s$ and standard deviation $\sigma_s$, 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, 2021) I assume that agents face a variable management fee for the stock portfolio.

**Participation Cost.** If an agent chooses to invest in the risky asset, she incurs a fixed per-period participation cost $\Phi$. 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 D.

## 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 (2021), 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.

[Insert Table 7 about here.]

## 4.2 Household Income Process

The household income process is given by the parameters $\overline{f_t}$, $\sigma_\zeta$, $\sigma_\epsilon$, $\sigma_\alpha$, $\lambda$, and $\kappa$. 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 C2. My estimates for $\overline{f_t}$ are very close to Cocco et al. (2005). Furthermore, I find $\sigma_\zeta$ to equal 0.117 and $\sigma_\epsilon$ to equal 0.290. These parameter values are similar to the ones estimated by Cocco et al. (2005) or Catherine (2021).

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

**Retirement Income.** The replacement rate in retirement $\lambda$ 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 $\kappa$ 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 is rather low. However, there is considerable uncertainty surrounding the average replacement ratio in the US (c.f. appendix C3) and some estimates by Martin (1996) indicate also very low values.

Furthermore, the actual probability $\omega_t$ of losing one's job within one year are taken from 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 Expectations.** 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 expectations. I estimate the subjective unemployment expectations 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 0.01 and the standard deviation equal to 0.159 which is the historical mean and volatility of the S&P500 since 1927. Furthermore, as usual in the literature I set the risk-free rate at 2 percent.

[Insert Table 8 about here.]

## 5 Structural Estimation

I target are the evolution of the unconditional and conditional risky share, participation rates, and wealth over the agent's life-time until retirement. 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]. The aim of the structural estimation is to elicit the unobserved parameters risk aversion ($\gamma$), discount factor ($\delta$), and participation cost ($\Phi$) 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 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 3 shows each of the empirical moments over the life-cycle. Similar to Catherine (2021), 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 E1). Depending on the specification, not all moments are targeted simultaneously. Intuitively, the discount factor ($\delta$) determines the wealth accumulation, risk aversion ($\gamma$) how much is allocated to the risky asset, and the participation cost ($\Phi$) deters households with low wealth levels to participate in the stock market.

# 6 Empirical 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 coefficient of relative risk aversion ($\gamma$) and the discount factor ($\delta$). Columns 1 and 3 of Table 9 display the estimated parameters for the baseline model with objective unemployment expectations and the model with distorted expectations, 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.

[Insert Table 9 about here.]

With objective unemployment probabilities, the agents require a relative risk aversion of 21.577 and a discount rate of 0.360 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 improves the estimated parameters considerably. The optimal parameters of risk aversion drops to 14.671, whereas the discount factor increases to 0.666. 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 4 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.

[Insert Figure 4 about here.]

Overall, the estimated parameters are even for the model with distorted expectations 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 $\delta$ 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 ($\gamma$) and the discount factor ($\delta$) as well as the participation cost ($\Phi$). 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 9 show the results of the estimation.

In the baseline model without distorted expectations, agents require a risk aversion parameter of 16.955 and a discount rate of 0.634 as well as a participation cost of 1.1 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 10.475. At the same time, the required discount factor increases to 0.720 and the participation cost increases to 2.4 percent. Once more, including distorted unemployment beliefs reduces the required risk aversion considerably. Similarly, the discount factor increases slightly.

Panel B of Figure 4 indicates a reasonable fit of both models. 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, 2021). Catherine (2021) proposes that heterogeneous participation cost would solve this problem. However, this is beyond the scope of this paper. Figure 4 also reveals that the fit of the participation rate in the model without distorted beliefs is significantly worse which is probably one of the reasons that the participation cost is slightly lower.

In conclusion, these findings demonstrate that including elicited unemployment expectations 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

Next, I explore the reasons for the improved fit of the model due to distorted unemployment beliefs in more detail. For that purpose, I compare the agent's policy functions of the baseline model and the model with distorted beliefs.

## 7.1 Comparison of Policy Functions

In this part, I further explore how distorted unemployment expectations affect an agent's policy functions and subsequently aggregate outcomes. Hence, figure 5 plots an agent's policy functions depending on her wealth. I assume that the agent exhibits a risk aversion parameter of 10 and a discount factor of 0.75 similar to what the structural estimation predicts. In the upper panel, I present the optimal risky share for the agent with objective expectations (left) and the agent with distorted beliefs (right) at the ages 25, 40, and 55.

The baseline agent optimally chooses to invest 40 percent of her assets after consumption into the risky asset only at very low levels of wealth. However, the share increases to 100 percent at intermediate levels of wealth. Subsequently, the optimal risky share decreases monotonically. This pattern of investing everything into the risky asset at low wealth levels and an decreasing share with increasing wealth is well documented in the theoretical literature and explains why it is so difficult to match the empirically increasing pattern of stock market participation with the traditional model. Younger individuals tend to be less wealthy and, hence, should invest all of their cash-on-hand into the risky asset. Interestingly, the low probability of actual unemployment is sufficient to prevent individuals at a young age and an intermediate level of wealth to invest everything into the risky asset.

[Insert Figure 5 about here.]

Conversely, the right panel presents the results for an agent with distorted beliefs. Overestimating the likelihood of job loss reduces the investment in the risky share considerably. This effect is especially pronounced at intermediate levels of wealth where the hump that reaches 100 percent investment in the risky share without distorted beliefs is reduced to around 60 percent. Hence, considering elicited beliefs creates close to an increasing function of the risky share in wealth as is observed empirically. This contrasts with the baseline model where the agent faces for most levels of wealth a downward sloping policy function. Importantly, the spike in risky investment at very low levels of cash-on-hand is covered in the model by the participation cost which prevents these agents from entering the stock market. On top of that, distorted beliefs reduce the share invested into the risky asset for young individuals by a significant 15 percent even at high levels of wealth. This further helps to match the low risky share younger individuals exhibit empirically.

Finally, the lower panel of Figure 5 reveals that the increased perceived labor income risk results in reduced consumption for a given level of wealth. However, this effect can only be observed at lower levels of wealth and younger ages. Intuitively, individuals with little savings or early on in their career prepare themselves for this disaster income shock by increasing their precautionary savings. Conversely, that means they increase their consumption.

Overall, these graphs shed further light on the mechanisms that improve the model fit when incorporating distorted beliefs. On the one hand, inflated unemployment expectations 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 levels of 2 to 5 times the permanent income. Comparing this with the model moments (c.f. Figure 4) 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. On the other hand, increased labor income risk also increases an agent's precautionary savings motive which translates into lower consumption and more saving in the risk-free asset. Hence, in principle the agent should accumulate more wealth over the life-cycle. However, this is counteracted by the agent foregoing on average higher returns by investing into the risky asset. Thus, the model with distorted beliefs does not significantly increase the required discount factor to match the evolution of wealth.

## 7.2 Policy Functions depending Unemployment Probability

Next, I explore how varying levels of unemployment probabilities affect the decision to invest in the risky asset depending on an agent's age. Figure 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. At relatively low levels of wealth, the agent should optimally invest all of his cash-on-hand into the risky asset. After reaching a very high level of wealth, 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 levels of wealth. Furthermore, investment in the risky asset is the lowest at low levels at wealth which is in line with the empirical evidence. Intuitively, these agents represent hand-to-mouth households which are hit the hardest by losing their job as they have no savings they can tap into in case of emergency. Hence, these agents need to optimally save more in the risk-free asset to ensure that they can maintain their level of consumption in the next period if the likelihood of job loss increases.

[Insert Figure 6 about here.]

Interestingly, the absolute level of the perceived job loss likelihood only matters for older individuals at a narrow window of wealth levels. 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 expectations vanishes after including a fixed per-period participation cost. The risky share drops to zero for these agents. Thus, the overall policy function becomes upward sloping at least for lower to intermediate levels of wealth.

In conclusion, three patterns emerge from the policy functions. First, introducing a perceived tail labor income risk via unemployment expectations is crucial to induce a risky share policy function that is close to becoming upward sloping in wealth. This is necessary to match the upward sloping risky share by age observed in the SCF data. Second, the level of unemployment expectations 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 expectations has a persistent negative effect on the optimal risky share across the whole wealth distribution for younger individuals. Hence, introducing distorted expectations is essential to generate the on average low levels of investment in the risky asset at young ages.

# 8 Conclusion

In this paper, I propose that taking expectations 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 expectations 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 expectations are highly persistent at low reported probabilities. Nevertheless, if an individual reports high levels of unemployment expectations, they quickly revert back to the low mean. Third, unemployment expectations 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 expectations in their portfolio optimization.

Taking all of these findings into account suggests that elicited unemployment expectations 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 expectations 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 expectations in the classic life-cycle model has the potential to greatly increase the model fit. Unemployment expectations are only a specific, yet important, expectation households have to form. Recent research has for example explored how subjective income growth (Rozsypal & Schlafmann, 2021) or subjective mortality beliefs (Heimer et al., 2019) help to improve theoretical models. However, households form a plethora of economic expectations 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 Figures

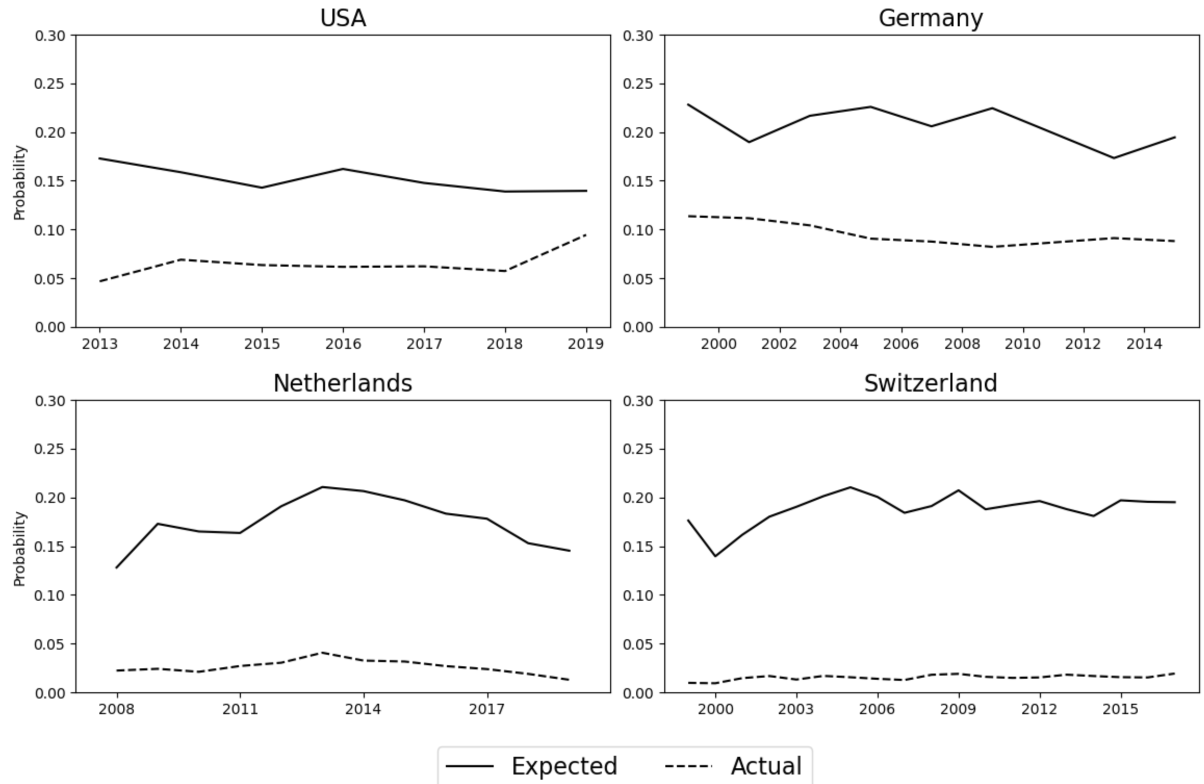


**Figure 1:** This figure plots the average subjective and objective probability of losing one's job for the SCE, GSOEP, LISS, and SHP. The solid line represents the average perceived probability of losing one's job within 12 months (24 months in the German data). Conversely, the dashed line shows the average actual probability of losing one's job within the next 12 months (24 months in the German data).

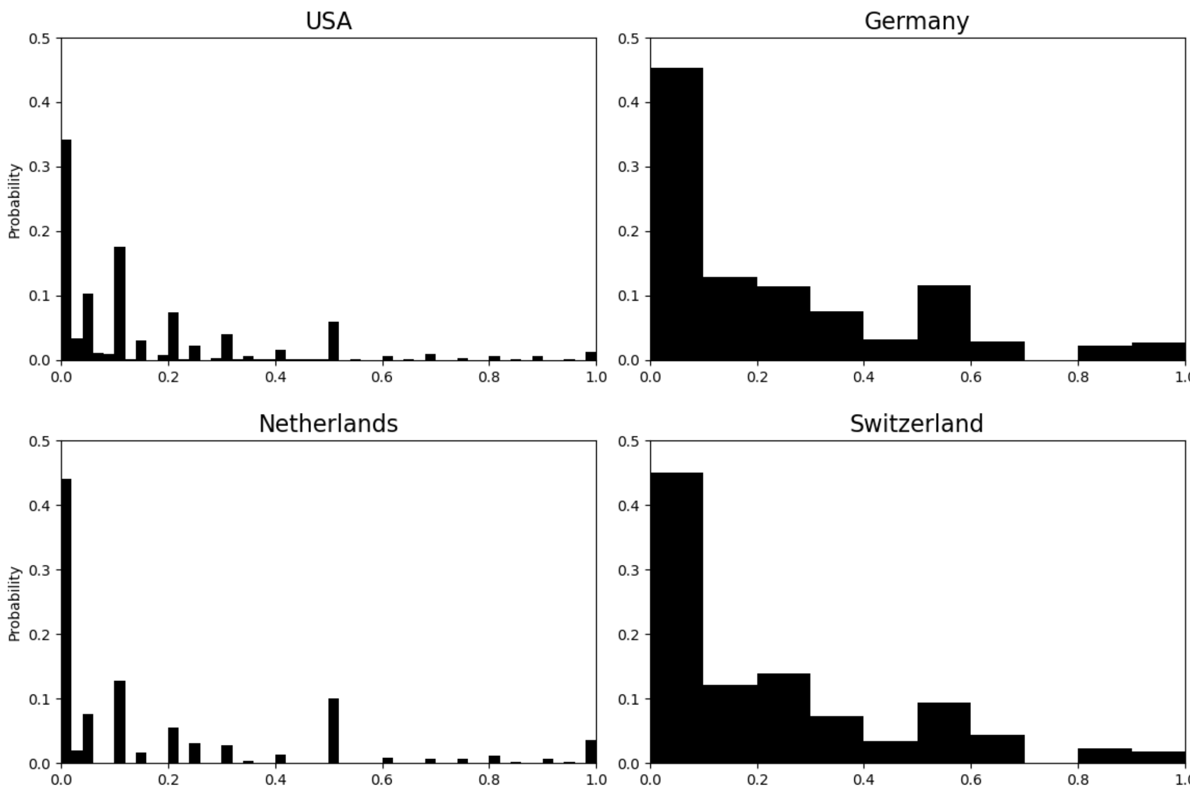


**Figure 2:** This figure plots the distribution of stated unemployment expectations for the SCE, GSOEP, LISS, and SHP. The subjective unemployment expectations are elicited on a continuous scale for the SCE and LISS. Conversely, the answers for the GSOEP and SHP are on a discrete scale in steps of 0.1.

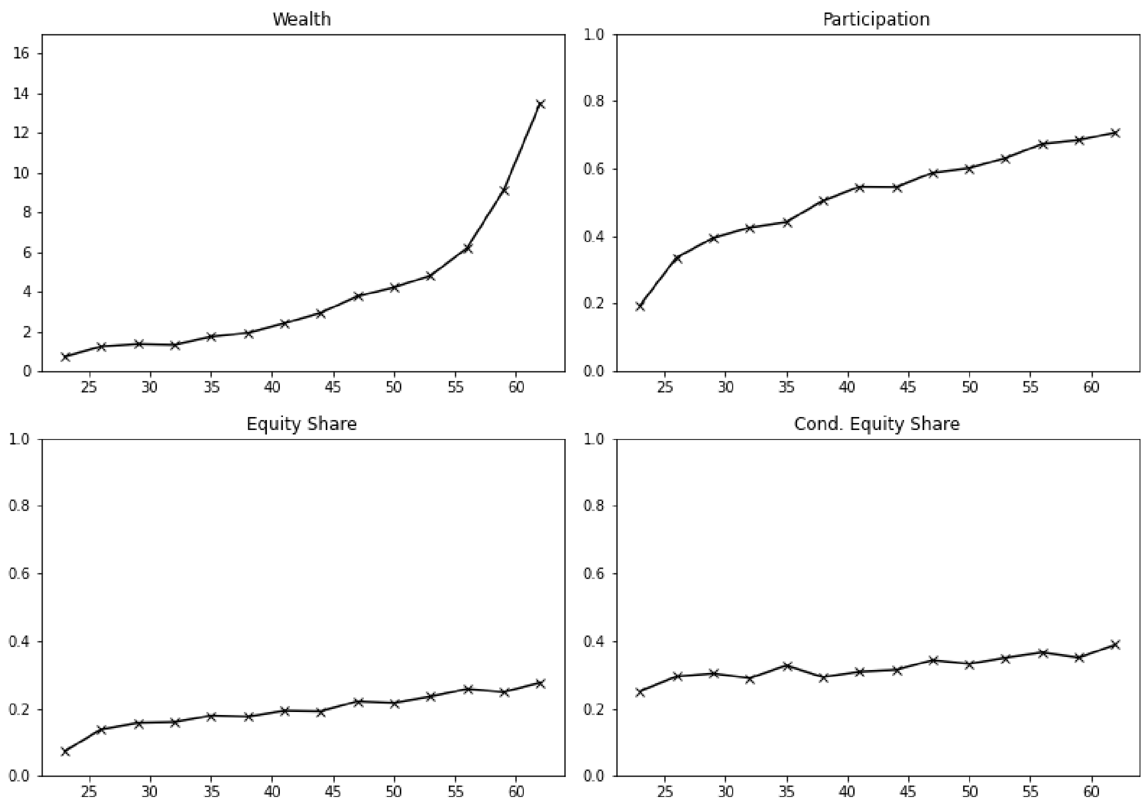


**Figure 3:** This figure shows the empirical moments estimated from the Survey of Consumer Finances (SCF). The upper left panel plots the evolution of wealth across 3-year age cohorts net of cohort and year effects. Equivalently, the upper right panel displays the participation rate, the lower left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

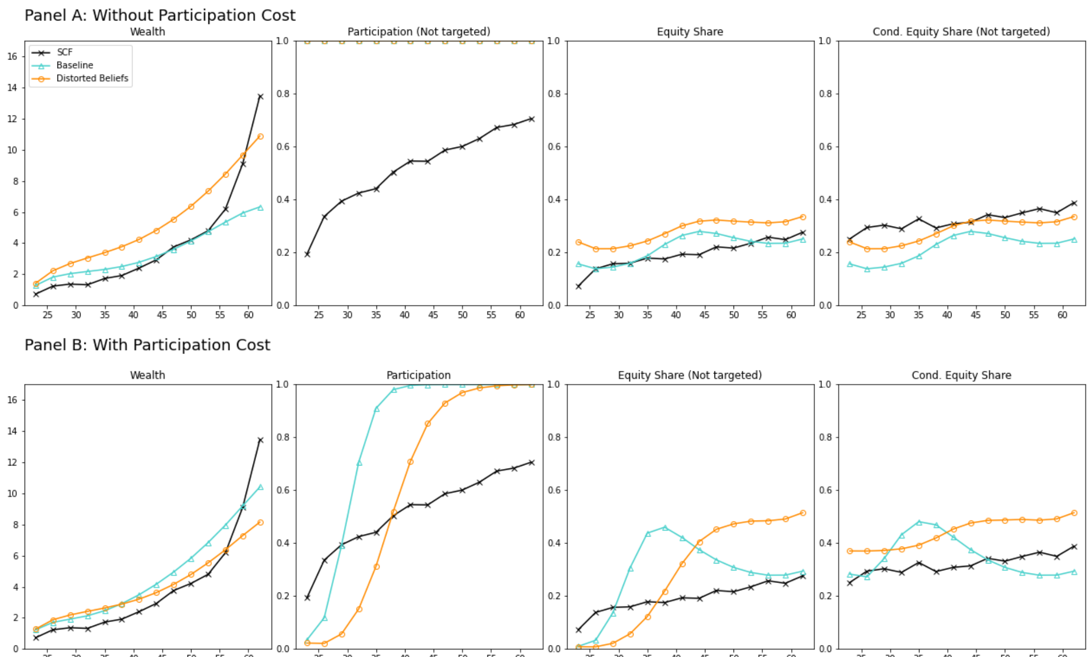


**Figure 4:** This figure shows the empirical moments (black) that are targeted by the structural estimation over the life-cycle as well as the estimated moments of the baseline model (green) and the model with distorted unemployment beliefs (orange). Panel A displays the moments for the model without 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.

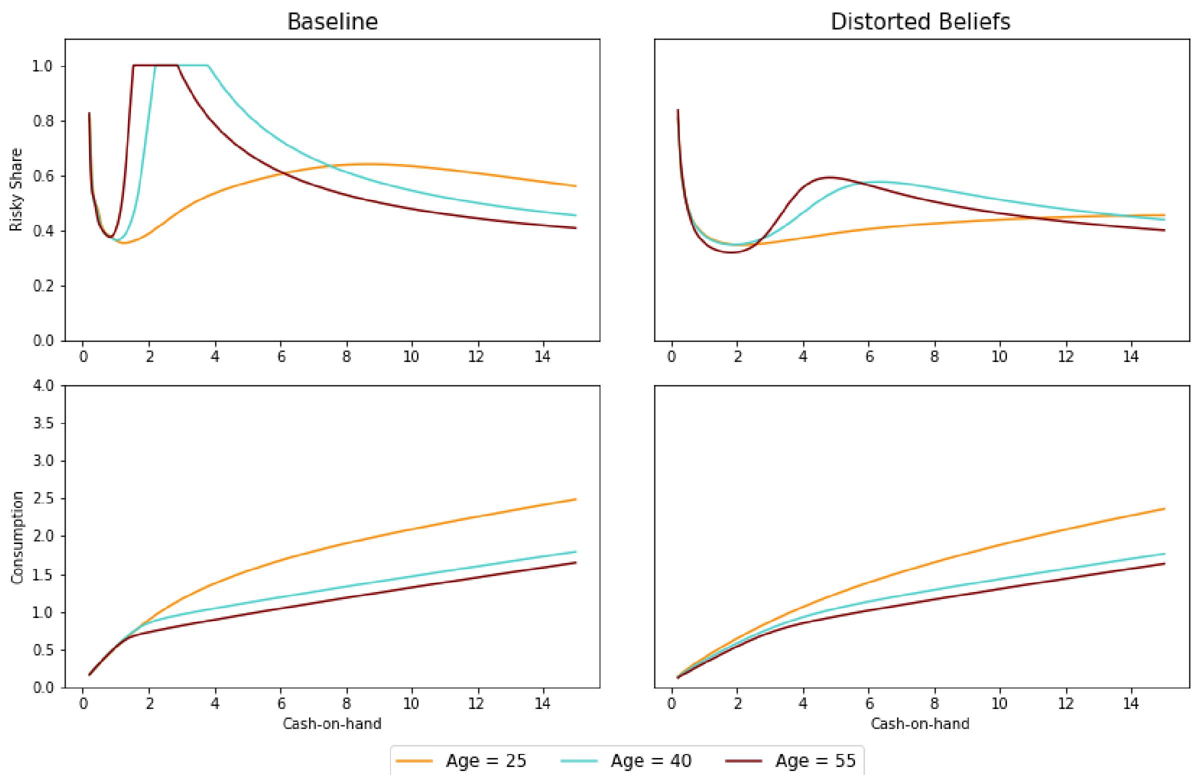


**Figure 5:** This figure shows the agent's optimal risky share and consumption depending on her cash-on-hand for various ages. The first column displays the policy functions for an agent that holds objective beliefs, whereas the second column presents them for an agent with distorted beliefs. The upper 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 agents are calibrated to have a relative risk aversion of 10 and a discount factor of 0.75.

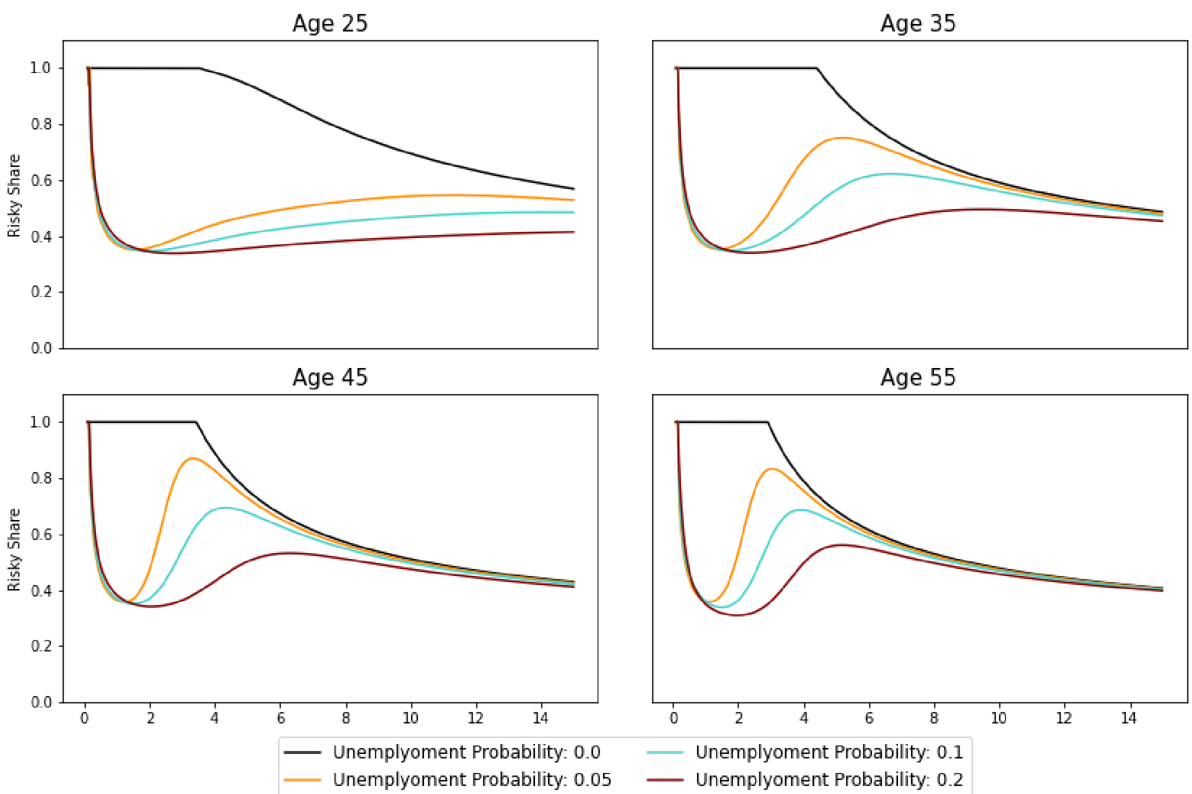


**Figure 6:** This figure displays the policy functions of four agents with varying levels of perceived unemployment probabilities for investing into the risky asset depending on the cash-on-hand. I plot the agents' policy functions at the ages of 25 (upper left), 35 (upper right), 45 (lower left), and 55 (lower right). The perceived unemployment probability is either 0 percent (black), 5 percent (orange), 10 percent (blue), or 20 percent (red). The agents are calibrated to have a relative risk aversion of 10 and a discount factor of 0.75.

# B Tables

**Table 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 | . | . | 1463.16 | 1252.45 | 1246.73 | 6095.91 | 4918.32 | 4942.13 |
| *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 |

**Table 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 | |
|---|---|---|---|---|---|---|---|---|
| | Expected | Actual | Expected | Actual | Expected | Actual | Expected | 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 |

**Table 3:** This table shows the results of regressing unemployment expectations on past unemployment expectations in the GSOEP, LISS, and SHP. In columns 1 and 2, I regress this years standardized unemployment expectations on standardized unemployment expectations stated two years ago. Conversely, in the remaining columns I regress this years standardized unemployment expectations on last years standardized unemployment expectations. 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 | |
|---|---|---|---|---|---|---|
| | Unemployment Exp. | | Unemployment Exp. | | Unemployment Exp. | |
| Unemp. Exp.(t-2) | 0.389*** | 0.391*** | | | | |
| | (68.51) | (68.49) | | | | |
| Unemp. Exp.(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 |

**Table 4:** This table shows how perceived unemployment expectations change from one year to the next in the GSOEP, LISS, SHP. Unemployment expectations are sorted into 5 bins increasing from 0 to 100 percent in steps of 20 percent. The rows represent last period's unemployment expectations and the column this period's unemployment expectations.

Germany

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | 0.73 | 0.15 | 0.08 | 0.01 | 0.03 |
| 2 | 0.35 | 0.37 | 0.20 | 0.04 | 0.04 |
| 3 | 0.24 | 0.26 | 0.37 | 0.06 | 0.07 |
| 4 | 0.24 | 0.22 | 0.33 | 0.10 | 0.10 |
| 5 | 0.33 | 0.20 | 0.24 | 0.07 | 0.16 |

Netherlands

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | 0.85 | 0.05 | 0.05 | 0.01 | 0.03 |
| 2 | 0.49 | 0.24 | 0.19 | 0.04 | 0.04 |
| 3 | 0.32 | 0.12 | 0.42 | 0.05 | 0.08 |
| 4 | 0.37 | 0.14 | 0.26 | 0.10 | 0.13 |
| 5 | 0.54 | 0.05 | 0.17 | 0.05 | 0.19 |

Switzerland

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | 0.76 | 0.14 | 0.05 | 0.02 | 0.02 |
| 2 | 0.36 | 0.42 | 0.15 | 0.04 | 0.03 |
| 3 | 0.23 | 0.26 | 0.35 | 0.10 | 0.06 |
| 4 | 0.20 | 0.22 | 0.30 | 0.18 | 0.10 |
| 5 | 0.30 | 0.17 | 0.21 | 0.11 | 0.21 |

**Table 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 expectation 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*** |
| Expectation | (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 |

**Table 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 expectations as well as an indicator variable if an individual is unemployed. Unemployment expectations are lagged by one year.´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. Risky Share | Cond. Risky Share | Parti- cipation | Parti- cipation |
|---|---|---|---|---|---|---|
| Unemployment | -0.006** | -0.006*** | -0.014** | -0.008* | -0.008 | -0.004 |
| Expectation(t-1) | (-2.10) | (-2.79) | (-2.02) | (-1.66) | (-1.20) | (-0.53) |
| Actual | -0.005 | 0.004 | -0.060 | -0.024 | -0.040 | -0.020 |
| Unemployment | (-0.33) | (0.34) | (-1.39) | (-0.73) | (-1.04) | (-0.50) |
| Person FE | NO | YES | NO | YES | NO | YES |
| Observations | 6,888 | 5,997 | 1,748 | 1,324 | 4,235 | 3,164 |
| Adjusted $R^2$ | 0.000 | 0.728 | 0.004 | 0.781 | 0.000 | 0.672 |

**Table 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 |

**Table 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 | $\mu_s$ | 0.082 | S&P500 historical returns |
| Standard deviation risky asset | $\sigma_s$ | 0.159 | S&P500 historical returns |
| Proportional management fee | | 0.01 | Catherine (2021) |
| Return on risk-free asset | $R_f$ | 1.02 | Catherine (2021) |
| *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 | $\sigma_\epsilon$ | 0.290 | PSID |
| Std. of permanent income shocks | $\sigma_\zeta$ | 0.117 | PSID |
| Std. of initial income distribution | $\sigma_\alpha$ | 0.139 | PSID |
| Unemployment probability | $\omega_t$ | | Choi et al. (2015) |
| Unemployment income | $\kappa$ | 0.065 | PSID |
| Replacement ratio | $\lambda$ | 0.671 | PSID |

**Table 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 expectations, whereas in columns 3 and 4 they hold distorted expectations. Additionally, columns 2 and 4 assume a fixed per period participation cost.

| | Baseline | | Distorted expectations | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Estimated Parameters* | | | | |
| Relative risk aversion | 21.577 | 17.221 | 14.671 | 10.475 |
| Discount factor | 0.360 | 0.632 | 0.666 | 0.720 |
| Fixed participation cost | | 0.011 | | 0.024 |
| *Panel B: Targeted life-cycle moments* | | | | |
| Risky share | ✓ | | ✓ | |
| Conditional risky share | | ✓ | | ✓ |
| Participation rate | | ✓ | | ✓ |
| Wealth | ✓ | ✓ | ✓ | ✓ |

# C Micro Data

## C1 Unemployment Expectations 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 expectations on a discrete scale from 0 to 10. However, the descriptive statistics in Table 2 reveal that unemployment expectations 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 expectation 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 expectations 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"?* |

## C2 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 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 $\sigma_\epsilon$ and $\sigma_\zeta$. 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 $\sigma_\zeta^2$ and the coefficient of the constant term is $\sigma_\epsilon^2$.

### C3 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.

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

# D 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. 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].

# E Simulated Method of Moments

## E1 Covariance Matrix of Moments

Following Catherine (2021), 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.

## E2 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 1200 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

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

stage estimates. I choose the 10 best estimates from the first stage estimates and make sure they converge to the same point.