# Perceived Income Risks

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**Abstract**

State-of-the-art incomplete-market macro models typically use the cross-sectional dispersion of income realizations from panel data to approximate the size of idiosyncratic risks and to make predictions about wealth inequality. But this practice runs into the problem of unobserved heterogeneity, as cannot perfectly approximate the true risks from the point of view of the agents. This paper, instead, uses a novel dataset of individual density forecasts of their wage growth and perceived unemployment risks to calibrate income risks in a standard OLG/incomplete-market model. Survey-implied income risks are more heterogeneous than commonly assumed, which makes it a new observable factor accounting for wealth inequality. Furthermore, perceived risks are lower than the conventional estimates, which helps explain why these models usually predict higher buffer stock savings than the actual data. These results are robust to a subjective model, where the perceived income risks driving saving decisions deviate from those that objectively govern income inequality.

**Keywords: Income risks, Incomplete market, Perceptions, Precautionary saving**

**JEL Codes: D14, E21, E71, G51**

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# 1 Introduction

Income risks matter for both individual behavior and macroeconomic outcomes. With identical expected income and homogeneous risk preferences, different degrees of risks lead to different saving/consumption and portfolio choices. This is well understood in models in which either the prudence in the utility function (Kimball (1990), Carroll and Kimball (2001)) or occasionally binding constraint induces precautionary savings or self-insurance. It is widely accepted based on various empirical research that idiosyncratic income risks are at most partially insured (Blundell et al. (2008)), such market incompleteness leads to ex-post wealth inequality[1] and different degrees of marginal propensity to consume (MPC) (Krueger et al. (2016); Carroll et al. (2017)). This also changes the mechanisms via which macroeconomic policies take effect[2]. Furthermore, the aggregate movements in the degree of idiosyncratic labor risks drive time-varying precautionary saving motives, as another source of business cycle fluctuations.[3]

The size and the heterogeneity of the income risks are one of the central inputs in this class of incomplete-market macroeconomic models. One common practice prevailing in this literature thus far is that economists typically approximate/estimate risks under a specified income process, relying upon the cross-sectional dispersion in income realizations, and then treat the estimates as the true model parameters known by the agents making decisions in the model.[4]

But this estimation practice has limitations. Economists who attempt to approximate the real size and persistence of unexpected income shocks and risks as perceived by the agents may very likely face omitted variables/unobserved heterogeneity and model mis-specification regarding its heterogeneity in risks. The intuition behind this is simple: some information, either intrinsic heterogeneity of each individual or advance information that enters an agent's information set from

[1] Aiyagari (1994); Huggett (1996); Carroll and Samwick (1997); Krusell and Smith (1998).
[2] Krueger et al. (2016), Kaplan et al. (2018), Auclert (2019).
[3] Challe and Ragot (2016); McKay (2017); Heathcote and Perri (2018); Kaplan and Violante (2018); Den Haan et al. (2018); Bayer et al. (2019); Acharya and Dogra (2020); Ravn and Sterk (2021); Harmenberg and Öberg (2021).
[4] Some recent examples include Krueger et al. (2016), Bayer et al. (2019), Kaplan et al. (2018).

time to time and is used to forecast her income, is not directly observable by economists. On the flip side, households making consumption decisions may have not fully incorporated all real-time information useful in forecasting their income, as usually assumed in standard models. As a result, the approximated risks by economists based on estimations are not identical to that as perceived by the agents and affect their saving decisions, leading to different predictions of their self-insurance behavior.

This paper attempts to address these issues by utilizing the recently available density forecasts of labor income surveyed by New York Fed's Survey of Consumer Expectation (SCE). The most important novelty of this paper compared to previous work studying partial insurance with expectational surveys [5] is that I use the density survey which contains directly perceived risks. In the density survey, respondents are asked to provide histogram-type forecasts of their wage growth over the next 12 months, together with a set of expectational questions about the macroeconomy. When the individual density forecast is available, a parametric density distribution can be fit to obtain the individual-specific subjective distribution. And the second moment, namely the implied variance of the subjective distribution, allows me to directly characterize the perceived risk profile without relying on external estimates from cross-sectional microdata. This provides the first-hand measure of perceived income risks that are truly relevant to individual decisions.

With the individual-specific reported perceived risk (PR) available, I can directly examine the cross-sectional heterogeneity in PR even within groups that conventional estimating methods assume to share the same degree of risks, such as education, age, and gender. I confirm that heterogeneity in PR does reflect between-group differences in idiosyncratic income risks, as revealed by estimates using panel data. For instance, younger, low-income, females, with low education with more volatile income growth also perceive higher risks. But despite controlling for these observable factors, people with the same observable characteristics are still widely dispersed in risk perceptions. A dominant share of the heterogeneity can be only attributed to unobserved heterogeneity/information. This

[5]For instance, Pistaferri (2001), Kaufmann and Pistaferri (2009).

suggests the importance of incorporating heterogeneity in income risks beyond a limited number of dimensions, such as education and age, as the standard practice in the literature.

This evidence motivates me to utilize survey-implied risks as truly perceived by agents to calibrate income risks in a standard incomplete market, overlapping-generation, and general equilibrium model to quantify these effects. The baseline model blends Huggett (1996), the income structure of Carroll and Samwick (1997), and persistent unemployment spells and unemployment benefits, a la Krueger et al. (2016) and Carroll et al. (2017). In comparison with conventional practice, I show how calibrating risks using surveyed PRs helps explain two well-documented discrepancies between standard model prediction and that seen in the data: the concentration of households with little liquid wealth, a large fraction of agents with high $MPC$, and more wealth inequality.

The mechanisms behind these two results are straightforward. First, allowing for heterogeneity in perceived income risks induces a straightforward increase in wealth inequality, as different risks induce different optimal savings. Second, a lower size of the perceived risks than in the baseline model implies less precautionary saving motive, hence lower buffer stock savings.

The benchmark model maintains the full-information-rational-expection (FIRE) assumption in that the perceived risks from the survey are used to calibrate the true model parameters, but in the extended model, I deviate from such an assumption.[6]. In particular, the extension allows the perceived risks (subjective risks) to be different from the underlying income process (objective risks). This extension achieves two purposes with one model. On the one hand, it serves as a robustness check with an alternative model assumption deviating from FIRE. On the other hand, it can be invoked as an intermediary to break down the model implications into two channels: one via ex-ante saving behavior resulting from risk perceptions and the other via ex-post realized income inequality.

[6]There is mounting evidence in macroeconomics that people form expectations in ways deviating from FIRE. For instance, Mankiw et al. (2003), Reis (2006), Coibion and Gorodnichenko (2012), Wang (2022), although most of these evidence are based on macroeconomic expectations such as inflation.

## 1.1 Related literature

First, this paper closely builds on the literature estimating both cross-sectional and time trends of labor income risks and the degree of partial insurance. Early work such as Abowd and Card (1989); Gottschalk et al. (1994); Carroll and Samwick (1997) started the standard practice in the literature of estimating income risks by decomposing it into components of varying persistence based on panel data. Subsequent work explores time-varying and macro trends of idiosyncratic income risks. For instance, Meghir and Pistaferri (2004) allowed for time-varying risks or conditional heteroscedasticity in the traditional permanent-transitory model. Blundell et al. (2008) used the same specification of income process to estimate partial insurance in conjunction with consumption data. More recently, Bloom et al. (2018) found that idiosyncratic income risks have declined in recent decades.[7] Moreover, recent evidence relying upon detailed administrative records and larger data samples highlighted the asymmetry and cyclical behaviors of idiosyncratic earning/income risks (Storesletten et al., 2004; Guvenen et al., 2014; Arellano et al., 2017; Guvenen et al., 2019; Bayer et al., 2019; Guvenen et al., 2021). Besides, a separate literature focus on job-separation and unemployment risks (Low et al., 2010; Davis and Von Wachter, 2011). In the Appendix, Table A.7 summarize the income process and estimated risks in a number of selected papers in this literature. Compared to this work, the novelty of this paper lies in the focus on the subjective perceptions of labor risks and how it is correlated with the realized income risks estimated from the income panel.

Closely related is the well-documented issue in the partial insurance literature: "insurance or information" (Pistaferri (2001), Kaufmann and Pistaferri (2009), Meghir and Pistaferri (2011), Kaplan and Violante (2010)). In any empirical tests of consumption insurance or consumption response to income shocks, there is always a concern that what is interpreted as the shock has actually already entered the agents' information set. On the contrary, agents may not instantaneously incorporate the innovations to income and the macroeconomy, although economists assume so, leading to the

[7]Although Moffitt (2020) found no such obvious trend for the same period by synthesizing various data sources.

excessive smoothness of supposedly anticipated shocks (Flavin (1988)). My paper shares a similar spirit with these studies in the sense that I try to tackle the identification problem in the same approach:[8] directly using the expectation data and explicitly controlling for what are truly conditional expectations of the agents. This helps economists avoid making assumptions about what is exactly in the agents' information set. What differentiates my work from other authors is that I directly use survey-reported income risks, which are available from density forecasts, instead of estimated risks using the difference between expectations and realizations. One advantage of the approach in this paper is that I can directly study individual-specific risks instead of the groups.

Third, the paper speaks to an old but recently reviving literature of studying consumption/saving behaviors in models incorporating imperfect expectations and perceptions. For instance, Pischke (1995) explored the implications of the incomplete information about aggregate/individual income innovations by modeling agent's learning about income component as a signal extraction problem. Wang (2004) extends the framework to incorporate precautionary saving motives. In a similar spirit, Carroll et al. (2018) reconciled the low micro-MPC and high macro-MPCs by introducing information rigidity of households in learning about macro news while being fully updated about micro news. Rozsypal and Schlafmann (2017) found that households' expectation of income exhibits an over-persistent bias, which may explain high MPCs out of transitory income shocks. More recently, Broer et al. (2021) incorporated information choice in a standard consumption/saving model to explore its implication for wealthy inequality. My paper has a similar flavor to all of these studies in that it also emphasizes the role of perceptions. But it has two major distinctions. First, this paper focuses on the second moment, namely income risks. Second, although most of this existing work explicitly specifies a mechanism of expectation formation deviating from the full-information-rational-expectation benchmark, this paper advocates for disciplining the model assumptions regarding belief heterogeneity by directly using survey[9] data.

[8] Recently, in the New York Fed blog, the authors followed a similar approach to decompose the permanent and transitory shocks.

[9] See Bhandari et al. (2019) for another example of directly using survey data to discipline subjective beliefs in

Besides, the paper is directly related to the research that advocated for eliciting probabilistic questions measuring subjective uncertainty in economic surveys (Manski (2004), Delavande et al. (2011), Manski (2018)). Although the initial suspicion concerning people's ability in understanding, using and answering probabilistic questions is understandable, Bertrand and Mullainathan (2001) and other works have shown respondents have the consistent ability and willingness to assign a probability (or "percent chance") to future events. Armantier et al. (2017) have a thorough discussion on designing, experimenting and implementing the consumer expectation surveys to ensure the quality of the responses. Broadly speaking, the advocates have argued for going beyond the revealed preference approach and the availability of survey data provides economists with direct information on agents' expectations and helps avoids imposing arbitrary assumptions. This insight holds for not only point forecast but also and even more importantly, for uncertainty, because for any economic decision made by a risk-averse agent, not only the expectation but also the perceived risks matter a great deal.

Finally, empirically, this paper is related to the literature studying expectation formation using subjective surveys. There has been a long list of "irrational expectation" theories developed in recent decades on how agents deviate from full-information rationality benchmark, such as sticky expectation, noisy signal extraction, least-square learning, etc. Also, empirical work has been devoted to testing these theories in a comparable manner (Coibion and Gorodnichenko (2012), Fuhrer (2018)). But it is fair to say that thus far, relatively little work has been done on individual variables such as labor income, which may well be more relevant to individual economic decisions. This paper shows that understanding the patterns of beliefs about individual variables, in particular, concerning both mean and higher moments, is fruitful for the macroeconomic modeling.

## 2 Theoretical framework

standard macro models.

## 2.1 Wage process and perceived risks

I primarily focus on the wage risk to be consistent with the survey-elicited question. Conditional on employment at the same job and position and same hours of work, the log idiosyncratic earning, or the wage rate, of an individual $i$ at time $t$, $w_{i,t}$ consists of a predictable component $z_{i,t}$ and a stochastic component $e_{i,t}$. (Equation 1)

$$w_{i,t} = z_{i,t} + e_{i,t} \tag{1}$$

There is an extensive discussion in the literature about the exact time-series nature of the stochastic component $e$. For instance, it may consist of a permanent and a transitory component.[10] Or some literature replaces the permanent component with a persistent component in the form of AR process.[11] The transitory component could be moderately serially correlated following a moving-average (MA) process.[12] I first proceed with the generic structure like in Equation 1 without differentiating these various specifications. I defer this discussion to Section 4.2.

Hence, wage growth from $t$ to $t+1$ consists of predictable changes from $z_{i,t+1}$, and those from realized wage shocks.

$$\Delta w_{i,t+1} = \Delta z_{i,t+1} + \Delta e_{i,t} \tag{2}$$

Under the assumption of full-information rational expectation (FIRE), all shocks that have realized till $t$ are observed by the agent at time $t$. Therefore, the expected volatility under FIRE

[10] Abowd and Card (1989),Gottschalk et al. (1994), Carroll and Samwick (1997), Blundell et al. (2008), and Kaplan and Violante (2010).

[11] Storesletten et al. (2004) and Guvenen (2009).

[12] Meghir and Pistaferri (2004).

(with a superscript $*$), or what this paper will refer to as perceived risks (PR), is the conditional variance of income growth from $t$ to $t+1$.

$$Var^*_{i,t}(\Delta w_{i,t+1}) = Var^*_{i,t}(\Delta e_{i,t+1}) \tag{3}$$

The predictable changes do not enter PR. Hence, the expected volatility in earning growth is the *conditional* variance of the change in the stochastic component. Notice here that $Var^*_t(\Delta e_{i,t+1})$ crucially depends on the time-series nature of $e_{i,t}$. Furthermore, in theory, this PR could be entirely specific to $i$, and it may not be equal to others' PR.

The size of the true PR, including the component-specific ones under a specified structure of $e_{i,t}$, is not directly observed by economists. Econometricians usually try to approximate it by subtracting observed wage growth in panel data $\Delta w_{i,t}$ by the approximated information set $\hat{\Delta} z_{i,t}$ available to the agent $i$ at time $t$. Furthermore, although in theory, the risk as perceived by a FIRE agent could be totally individual-specific, economists can only approximate them at the group level, which we hereby refer to as $c$, as there are no realizations of risks, but only stochastic outcomes, at individual level. For instance, $c$ could be defined based on age, gender, education or the years of entering job markets. (Equation 4)

$$Var_c(\Delta \hat{e}_{i,c,t}) = Var_c(\Delta w_{i,c,t} - \Delta \hat{z}_{i,c,t}) \tag{4}$$

Specifically, in this estimation, what is used as an approximation of the stochastic component $e$ and later further decomposed into various components of time persistence, is the regression residual of individual wage on all the observable characteristics of the individual in a first-step regression. Economists could not perfectly know all the predictable components $z_{i,t}$ from the agent's point of view. They instead include in $\hat{z}_{i,t}$ factors such as age polynomials, gender, education, occupation, etc. Denote the regression-residual or the approximated stochastic component by $\hat{e}_{i,t}$.

Unlike the PR of the agent, the cross-sectional variance of the change in residuals within group $c$, $Var(\Delta \hat{e}_{i,c,t})$, usually referred to as the "income volatility" in the literature, [13] is an *unconditional* variance at the group level.

The distinction between the *conditional* PR by the agent and the *unconditional* volatility approximated by the economists is crucial. There are two important issues around the comparability of the two objects.

First, it is very likely that what is controlled for in the first-step income regression, namely $\hat{z}_{i,c,t}$, does not perfectly coincide with what is *predictable* from the point of view of an FIRE[14] agent at time $t$. The primary reason is that econometricians with the panel data of earnings cannot control for other "unobserved heterogeneity" that is not measured in the data. This is equivalent to the "superior information" problem, [15] which refers to the possibility that agents have advance information or foresight regarding their earning growth that is not available to econometricians. For instance, a worker may already anticipate a recent dispute with her boss may negatively affect her earning next year, but econometricians have no way of knowing this.

Second, the comparison is sensitive to the time-series nature of $e_{i,c,t}$. This is, again, because economists' estimated volatility is unconditional, while the perception is conditional on the information till time $t$. To illustrate this point, imagine there is a very persistent component in the income shock, then under the aforementioned process, the estimated income volatility also includes the variance of the realized shock till $t$, which enters the information set of the agents already. Therefore, even if the econometricians perfectly recover the $e_{i,c,t}$ in the first step regression, any differences in the perceived time-series nature of the $e_{i,c,t}$ by agents and econometricians would lead to differences between PR and income volatility. Therefore, to approximate the true PR from the point of view of agents, economists need to recover a conditional variance using information from the

[13]For instance, Gottschalk et al. (1994), Moffitt and Gottschalk (2002), Sabelhaus and Song (2010), Dynan et al. (2012), Bloom et al. (2018).

[14]In later sections of the paper, I relax the FIRE assumption, which it makes it possible that PR reported in the survey is also subject to incomplete information and behavioral bias of the agents.

[15]Pistaferri (2001); Kaufmann and Pistaferri (2009).

unconditional variance, typically by assuming a time-series structure of the stochastic component $e$. I return to this discussion in Section 4.2.

To summarize, this paper argues that there are two major reasons why survey-elicited PR has invaluable use and is preferable to the conventional income risk estimation based on cross-sectional realizations, which is further used to parameterize macro models. First, survey-reported PR is, by construction, conditional on the information set of each agent $i$, which very likely includes intrinsic heterogeneity specific to the individual or the advance information useful to forecasting her own wage growth.[16] Economists who try to approximate the PR cannot do as well as the agents answering the questions, simply because this information is not necessarily available to economists. Second, survey-implied PR provides direct identification of the degree of heterogeneity of income risks across individuals in the economy. This prevents modelers from making possibly imperfect assumptions to estimate group-specific income risks, by grouping individuals by very limited dimensions of observable factors, such as education and age.

It is worth pointing out that despite these advantages of the survey-implied PRs, they are admittedly subject to the measurement errors and behavioral bias of agents in the real world compared to that is assumed by FIRE. I will explore the robustness of results of the paper with respect to these alternative assumptions in both estimation and models.

# 3 Data, variables and density estimation

## 3.1 Data on perceived risks

The data used for this paper is from the core module of the Survey of Consumer Expectation(SCE) conducted by the New York Fed, a monthly online survey for a rotating panel of around 1,300 household heads over the period from June 2013 to July 2021, over a total of 97 months.

[16] For the same reason, the literature partial insurance proposes to use expectational surveys, as one resolution of the superior information problem. See Pistaferri (2001), Kaufmann and Pistaferri (2009) and others for examples.

I primarily rely upon the density forecast of individual earnings by each respondent in the survey to estimate perceived income risks. In particular, the main question used is framed as the following: "Suppose that 12 months from now, you are working in the exact same ["main" if Q11>1] job at the same place you currently work and working the exact same number of hours. In your view, what would you say is the percentage chance that 12 months from now, your earnings on this job, before tax and deductions, will increase by x%?".[17] Then, I fit the bin-based density forecast in each survey response with a parametric distribution. [18] The variance of the estimated distribution naturally represents an individual-specific perceived risk.

Crucially, as the survey question regards the expected earning growth conditional on the same job position, same hours, and the same location, it can be clearly interpreted as the wage. It becomes immediately clear that wage risk only constitutes a part of income risks. This has two important implications.

First, focusing on the wage risks avoids the problem of confusing earning changes due to voluntary labor supply decisions as risks. Empirical work estimating income risks is often based on data from total earnings or total household income, in which voluntary labor supply decisions inevitably confound the true degree of uninsured idiosyncratic risks. As it is clear regarding the wage, this survey-based measure used here is not subject to this problem. Meanwhile, however, the wage risk also excludes important sources of income risks such as unemployment and job switching. Such major transitions in job career, as some existing research (for instance, Low et al. (2010)) has shown, are oftentimes the dominant source of income risks facing individual workers. I separately examine unemployment/separation expectations, both of which are surveyed in SCE as well in Section 4.4.

[17]As a special feature of the online questionnaire, the respondent can move on to the next question only if the probabilities filled in all bins add up to one. This ensures the basic probabilistic consistency of the answers crucial for any further analysis.

[18]This follows the approach by Engelberg et al. (2009) and the researchers in the New York Fed (Armantier et al. (2017)). Appendix A.1 documents in details the estimation methodology and its robustness.

## 3.2 Wage data

I use longitudinal data on individual labor earnings from the 2014-2017 and 2018-2020 panels of the Survey of Income and Program Participation (SIPP).[19] Each panel of the SIPP is designed to be a nationally representative sample of the U.S. population and surveys thousands of workers. The interviews are conducted once a year to collect the individual's monthly earnings and labor market activity[20]. On average, each individual is surveyed for 33 months over the multiple waves of the survey.

For the purpose of this paper, there are obvious advantages with using SIPP over another commonly used dataset for income risk estimation, the most notable of which is the Panel Study of Income Dynamics (PSID). SIPP surveys monthly labor outcomes of workers such as earnings, hours of work, other detailed records of job transitions and unique employer identifier, while PSID only provides biennial records of labor income for years since 1997. For the overlapping periods between SIPP and SCE, it is possible to make a direct comparison between realized wage risks at the annual frequency and the ex-ante perceptions of the wage risks. This is particularly crucial if wage risks are time-varying and dependent upon macroeconomic conditions.

For an apples-to-apples comparison, I obtain the hourly wage of workers with the same employer by dividing the total monthly earnings from the *primary job* by the average hours of work for the same job for those who only stay with the same employer for at least 2 years. I follow the same approach as in Low et al. (2010) to identify job stayers. In addition, I impose the following criteria. (1) only working-age population between 25-65. (2) only private-sector jobs, excluding workers from government or other public sectors. (3) no days away from work during the reference month without the pay. (4) the same job as the last year. (5) monthly wage rates that are greater than 10 times

[19] Other recent work that estimates income risks using SIPP includes Bayer et al. (2019). Different from this paper, they use quarterly total household income, instead of the monthly job-specific earning of individuals.

[20] This causes the "seam" issue well documented in the survey literature(Moore, 2008)., which states that cross-wave transitions are systematically larger in magnitudes than within-wave changes. Therefore, I exclude the December-to-January earning growth in estimations to address this issue.

or smaller than 0.1 times of the average wage are excluded. This leaves me with a monthly panel of 350-1000 individual earners for the sample period 2013m3-2019m12. Appendix A.3 discusses the data selection and summary statistics in greater details.

# 4 Basic facts of perceived income risks

## 4.1 Observable and unobservable heterogeneity

In both income risk estimation and parameterization of the standard incomplete market macro models, it is common practice to assume idiosyncratic risks differ by certain observable factors such as education, gender, and age, and furthermore, there is no additional within-group heterogeneity in the degree of the risks.[21] This section reports the finding that although the observed heterogeneity in PR across individuals does reflect between-group differences along dimensions economists have commonly assumed, a dominant fraction of the differences in PR is attributed to other unobservable heterogeneity. Furthermore, even in those observable dimensions, the group heterogeneity seen in PR does not coincide with that seen in estimated risks.

Figure 1 plots the group average of perceived risk, approximated wage volatility $Var(\Delta\hat{e})$ as defined in Equation 4, and the estimated risk $Var_t(\Delta\hat{e})$ by age, gender and education. As to the education-risk profile, both wage volatility and approximated risks are higher for more educated workers. This is consistent with the finding of Meghir and Pistaferri (2004) using labor income instead of wage. In contrast, risk perceptions exhibit the opposite pattern with respect to education level, in that less-educated workers perceive wage risks to be higher than more-educated workers. As to the life-cycle pattern of risks, neither wage volatility nor estimated risks shows a monotone

[21]For instance, Meghir and Pistaferri (2004) found that more educated workers are faced with higher income risks than the less educated ones. In addition, Sabelhaus and Song (2010) and Bloom et al. (2018) documented that income risks decrease with age, and vary with the current income level in a non-monotonic U-shape. Cagetti (2003), Blundell et al. (2008), and Carroll et al. (2017) allowed for heterogeneous risks across different demographic variables in their models.

pattern over the life cycle.[22] In contrast, perceived risks nearly monotonically declines over the life cycle for both males and females. These findings are also confirmed in Table A.6, which reports the group average of PR, wage volatility and estimated risks.

Another salient fact is that PR is always smaller than estimated risks. In particular, both wage volatility and estimated risk of different groups fall in the range of 5-15% per year (in standard deviation), which broadly aligns with the estimates in a large literature and that used in models, as summarized in Table A.7. But the average perceived risks reported in the survey is only around 3-4%, at least half smaller. For instance, a male high school graduate on average perceives annual wage risk to be 4 percentage points in terms of standard deviation, while the income risk implied by wage panel data for the same group is above 9-10 percentage points.

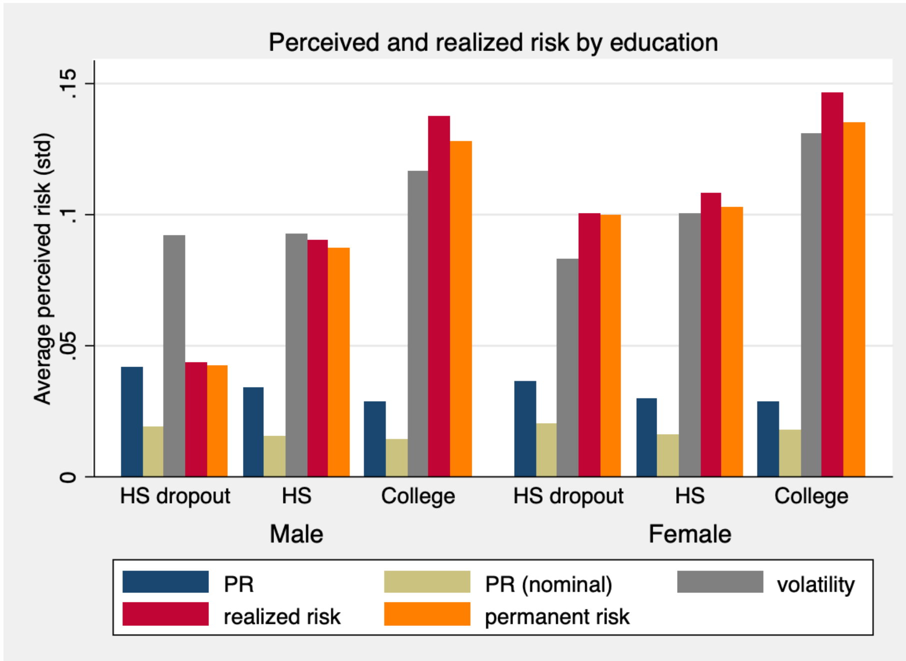
But despite controlling for all the observable factors of the individuals, there remains a large degree of heterogeneity that seems to be most likely attributable to other unobserved factors. Figure 2 shows the sizable dispersion of the unexplained residuals of PRs both in nominal and real terms after controlling for observable individual characteristics including age, age polynomial, gender, education, type of work, and time fixed effects, respectively. Controlling for the time fixed effects is important because the focus here is on the idiosyncratic risks perceived by agents.

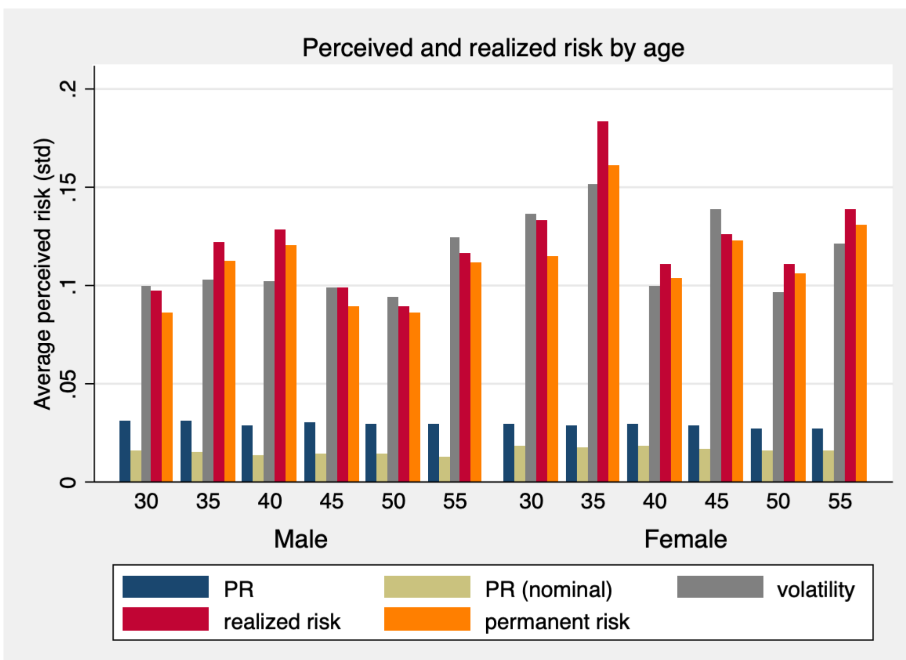
In both nominal and real terms, the distribution is right-skewed with a long tail. Specifically, most of the workers have perceived a standard deviation of nominal earning growth ranging from zero to 4% wage growth a year). But in the tail, some of the workers perceive risks to be as high as $7-8\%$ standard deviation a year. To have a better sense of how large the risk is, consider a median individual in our sample, who has an expected wage growth of 2.4%, and a perceived risk of 1% standard deviation. This implies by no means negligible risks. [24]

[22]The homogenous age pattern of wage risks is not necessarily contradictory with the well documented declining pattern estimated using data on household income or total earning[23]. It is likely that the decline of income risks over the life cycle has to do with non-wage risks or better insurance via work arrangements over the life cycle.

[24]In the Appendix A.2.1, I also include histograms of expected income growth and skewness, which shows intuitive patterns such as nominal rigidity. Besides, about half of the sample exhibits non-zero skewness in their subjective distribution, indicating asymmetric upper/lower tail risks.

**Figure 1:** Perceived Risks, Wage Volatility and Estimated Wage Risks by Observable Factors

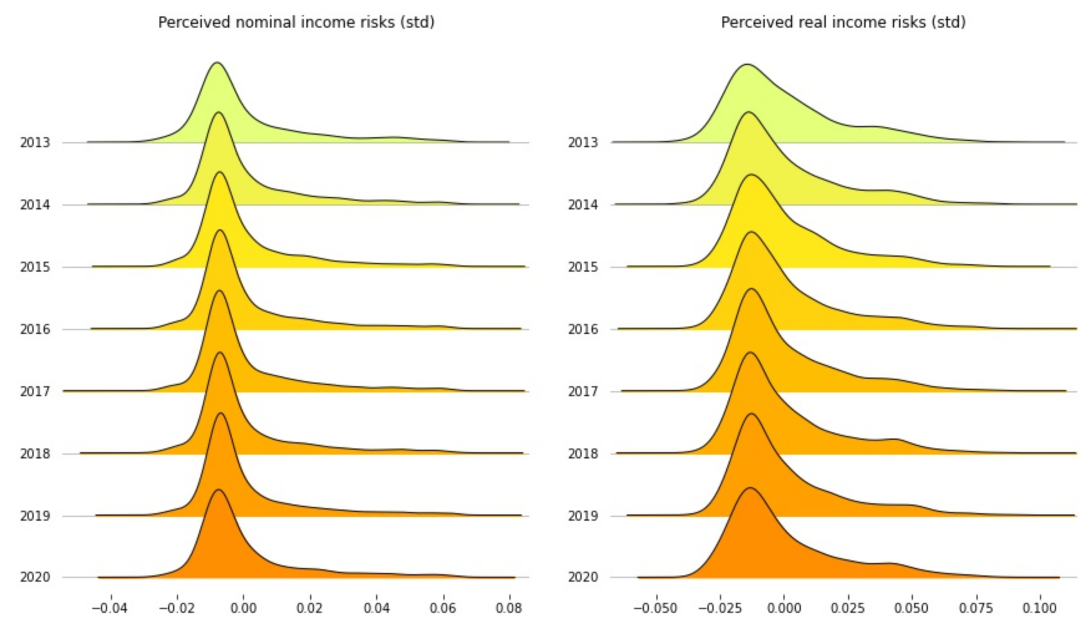



Note: this figure plots perceived risk (from SCE), average estimated wage volatility, approximated wage risk, and permanent risk (from SIPP) of each education-gender (upper panel) or age-gender (bottom panel) group. The volatility is approximated by the within-group cross-sectional standard deviation of log changes in unexplained wage residuals, as defined in Equation 4. The estimated risk is based on the process specified in Equation 6.

Besides observable factors controlled in the first-step regression, individual fixed effects are important in explaining the heterogeneity in PRs. In particular, the $R^2$ of the regression without individual fixed effects is at most 10%, while including fixed effects increases $R^2$ to 70%. This finding has two implications. First, the role of unobservable heterogeneity seems to suggest that the conventional practice of estimating and modeling income risks differently by demographic groups has limitations. Second, the survey-implied heterogeneity in PR can be directly put into use to model heterogeneous income risks without requiring a strong stance on the explanations of the source of heterogeneity. Therefore, the model calibration in Section 5 adopts such an approach.

**Figure 2:** Dispersion in Unexplained Perceived Income Risks




Note: this figure plots the distributions of residuals of the perceived standard deviation of 1-year-ahead earning growth in nominal (left) and real terms (right) after controlling for age, age polynomial, gender, education, type of work arrangement, and time fixed effects. The real risk is the sum of the perceived risk of nominal income and inflation uncertainty.

## 4.2 Decomposed risks of different persistency

One crucial aspect of income risks relevant to both economists' estimation and household decisions is its time-series nature. As to the former, perceived income risks by the agents at a particular point of time, say $t$, are conditional on the information that is available by $t$. A realized permanent/persistent shock carries information regarding future income growth path, while an entirely transitory shock does not. Therefore, in the two scenarios, agents perceive different degree of income risks. For the latter, permanent income risks affect consumption/savings more substantially than the transitory risks via induced precautionary saving motives, according to the Permanent-Income Hypothesis (PIH).

I follow a large body of literature [25] to specify the stochastic component $e_{i,c,t}$ to consist of a permanent component $p$ which follows a random walk and a transitory component $\theta$. The shocks to both components are log normally distributed, with mean zero and time-varying risks.[26]

$$\begin{aligned} e_{i,c,t} &= p_{i,c,t} + \theta_{i,c,t} \\ p_{i,c,t} &= p_{i,c,t-1} + \psi_{i,c,t} \end{aligned} \tag{5}$$

In particular, under such a specification, the observed income volatility defined as in Equation 2, $\text{Var}(\Delta \hat{e}_{i,c,t})$ is essentially the sample analogue of the following.

$$Var(\Delta e_{i,c,t}) = \sigma^2_{\psi,t} + \sigma^2_{\theta,t-1} + \sigma^2_{\theta,t} \tag{6}$$

The estimated perceived income risks under full-information rational expectation (FIRE) would be exactly the summation of the variance of the two components $\sigma^2_{\psi,t} + \sigma^2_{\theta,t}$. The difference between the perceived risks and the income volatility, $\sigma^2_{\theta,t-1}$ is exactly due to the fact that the former is unconditional variance and the latter is conditional on the information available to the agent at the time $t$.

Using the same identification strategy in the literature [27], I identified the time-varying variances

[25] Abowd and Card (1989), Gottschalk et al. (1994), Carroll and Samwick (1997), Blundell et al. (2008), etc. Crawley et al. (2022) presents a more parsimonious process to resolve the possible model mis-specification caused by"time-aggregation" problem.

[26] This also corresponds to the model specification as in Equation 14.

[27] See Appendix A.4.1 for details of the identification strategy, which follows Abowd and Card (1989); Carroll and Samwick (1997); Meghir and Pistaferri (2004); Blundell et al. (2008). Essentially, this approach relies upon moment conditions as that in Equation 6 and the auto-covariance terms of $\Delta e_{i,c,t}$ to pin down the time-varying sizes of $\sigma_\psi$ and $\sigma_\theta$.

of the permanent and transitory component of the monthly wage growth, i.e. $\sigma^2_{\psi,t}$ and $\sigma^2_{\theta,t}$, using the $SIPP$ data for the same period. Then I convert these monthly risks parameters into annual frequency to be compared to perceived risks about annual risks.[28] Appendix A.4.3 provides alternative estimates for quarterly and yearly frequency.

Figure 3 plots the 1-year-ahead perceived income risks reported in the $SCE$ against the estimated *realization* of the total, permanent and transitory risk for the same period. Under correct model-specification and FIRE of the agents, one may expect the perceived risks and expected volatility to be, if not equal, at least close to each other. But the results suggest there is a negligible correlation between the two series.

More importantly, the magnitudes of the perceived risks are significantly lower than the expected income volatility implied by the income risks estimations. For instance, the latter based on the full sample should be 10% in standard deviation a year, while the average earning risk perception in $SCE$ is only 2%. The same pattern holds even if we separately estimate income risks for different gender, education and age. (See Table A.6.)

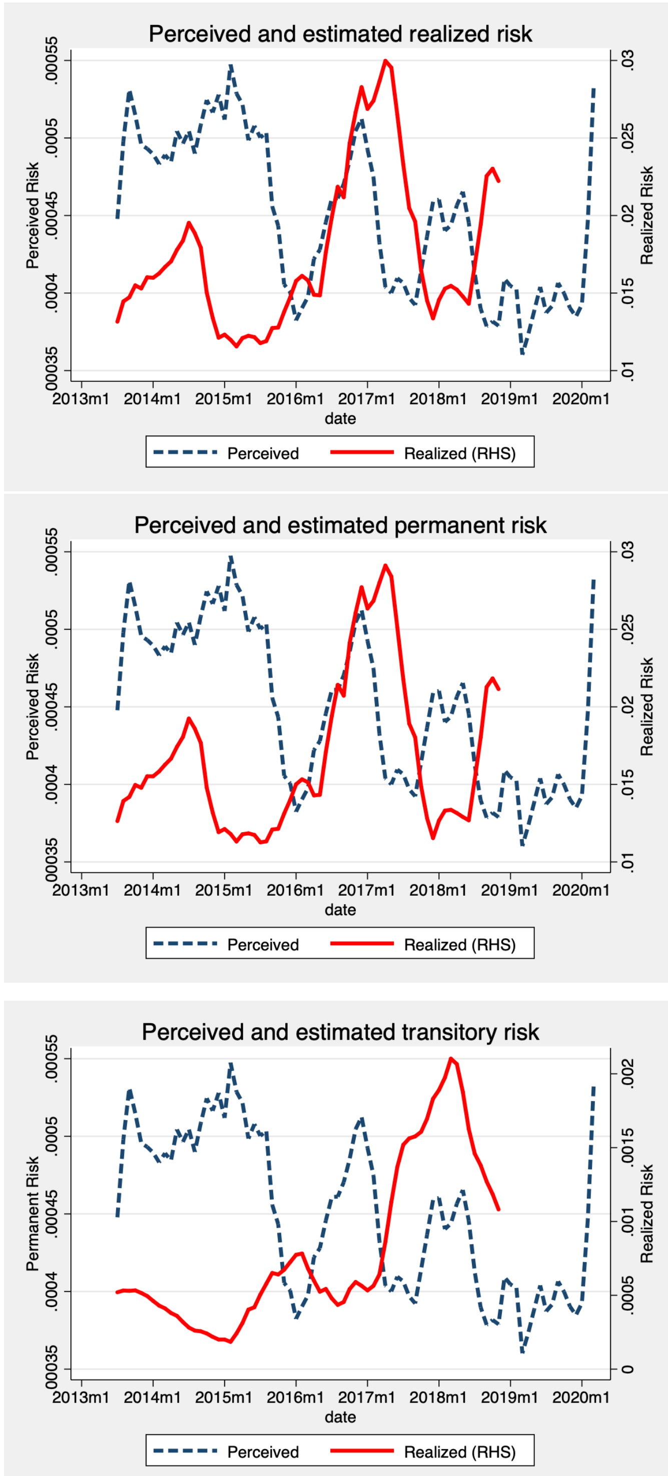
The most likely explanation for such a disconnect in both size and time-varying pattern between the two series is unobservable heterogeneity or superior information, as elaborated in the next section. The later part of the paper provides additional evidence that the survey-reported risk perceptions are better at explaining consumption-saving behaviors and generating the observed wealth inequality seen in the data than the economists' estimates.

## 4.3 Accounting for the evidence

This section proposes a preferred explanation in this paper for the size differences between individual PRs reported in the survey and that estimated using panel data, which is the role of unobserved

[28] For permanent risks, the annual earning risk is the summation of monthly permanent risks over the next 12 months. The transitory risks of annual earnings, in contrast, is the sample average of monthly risks over the next 12 months.

**Figure 3:** Perceived and Realized Risks




Note: this figure plots median 1-year-ahead perceived income risks in the whole SCE sample against the estimated realized risks, permanent, and transitory risks over the *same* period. Both series are regarding the real wage. The realized risks are first estimated monthly from SIPP and then aggregated into annual frequency. Specifically, the permanent risks are the sum of monthly permanent risks and the annual transitory risks are the simple average over the corresponding 12 months.

heterogeneity or advance information. In the model section 6, I explore alternative hypotheses, such as mis-perception of risks by agents due to behavioral bias.

For clarity, I simplify the same wage process specified in Equation 5 by assuming away the time-variation of the risks. Furthermore, all agents have individual-specific permanent $\sigma^2_{i,\psi}$ and transitory risks $\sigma^2_{i,\theta}$, hence, perceived income risks, but have the same relative size of the two $\kappa$. Individual $PR$s follow a log-normal distribution with mean $\mu_{\text{PR}}$ and standard deviation $\sigma_{\text{PR}}$.

$$\log(\text{PR}_i) \sim N(\mu_{\text{PR}}, \sigma^2_{\text{PR}}) \tag{7}$$

The two parameters can be straightforwardly estimated by fitting a log-normal distribution to the cross-sectional distribution of the time-average PRs in SCE, as shown in Figure 4, where both the SCE distribution and the fitted log normal distribution are plotted.

When economists try to estimate the wage risks using panel data, we cannot estimate individual-specific risks. Instead, we can only identify the *average* permanent and transitory risks at the population level, relying upon the cross-sectional and auto-covariance of the approximated income residuals $\Delta\hat{e}_{i,t}$.

To capture unobserved heterogeneity explicitly, I allow for the unexplained income residual change $\Delta\hat{e}_{i,t}$ to be different from what is truly unpredictable from the individual $i$'s point of view, $\Delta e_{i,t}$, by exactly $\xi_{i,t}$. To be entirely consistent with the wage process, one can assume that it consists of a corresponding permanent component $\xi^{\psi}_{i,t}$ and a change in transitory component $\Delta\xi^{\theta}_{i,t}$. For instance, one of the reasonable interpretations of the permanent component of $\xi^{\psi}_{i,t}$ is the individual-specific growth rate in permanent income, which cannot be observed by researchers. An example of the transitory changes in the unobserved component could be temporary wage cuts.

$$\Delta\hat{e}_{i,t} = \Delta e_{i,t} + \xi_{i,t} = \psi_{i,t} + \Delta\theta_{i,t} + \xi_{i,t} = \psi_{i,t} + \Delta\theta_{i,t} + \xi^{\psi}_{i,t} + \Delta\xi^{\theta}_{i,t} \tag{8}$$

It is easy to show that except for a special case absent of such unobserved heterogeneity captured by $\sigma^2_{\xi,\psi} = \sigma^2_{\xi,\theta} = 0$, the common GMM procedure in the literature can only recover an upward-biased PR from these estimates with the difference being exactly the variance due to the unobserved heterogeneity.[29]

$$\widehat{\mathrm{PR}} = \int \mathrm{PR}_i + \sigma^2_\xi = \int \sigma^2_{i,\psi} + \int \sigma^2_{i,\theta} + \underbrace{\sigma^2_{\xi,\psi} + \sigma^2_{\xi,\theta}}_{\text{unobserved heterogeneity}} \tag{9}$$

The total size of the unobserved heterogeneity $\sigma^2_\xi \equiv \sigma^2_{\xi,\psi} + \sigma^2_{\xi,\theta}$ can be directly identified by taking the difference between average PR from SCE and that is approximated based on panel data estimation (plotted as the difference between the two vertical lines in Figure 4. Furthermore, with an auxiliary assumption that the two unobserved terms have the same ratio as $\kappa$, then we can further decompose the estimated heterogeneity into $\sigma^2_{\xi,\psi}$, and $\sigma^2_{\xi,\theta}$, regarding the permanent and transitory wage shock, respectively.

With the standard estimates of $\sigma_\psi = \sigma_\psi = 0.15$, hence $\kappa = 1$, the procedure produces corresponding estimated heterogeneity in PRs and the size of unobserved heterogeneity, as plotted in Figure 4. I use these estimates to calibrate the model in the following sections.

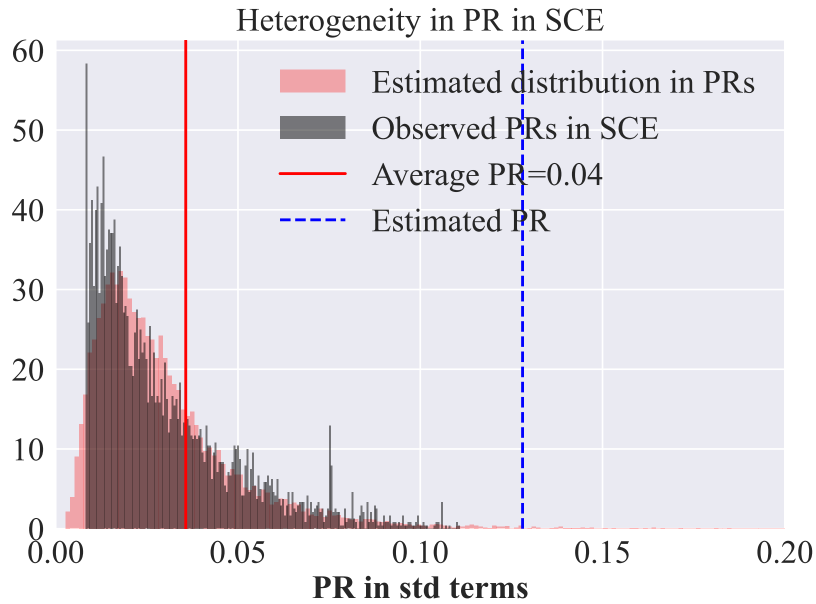
## 4.4 Unemployment risk perceptions

The analysis so far only focuses on wage risks conditional on staying in the same job. But it admittedly only constitutes a part of the income risks, since major labor market transitions such as job loss and switching usually result in more significant changes in labor income and affects a household's welfare.[30] Unemployment risks are usually another central input of the incomplete-market macroe-

[29]The proof: the common GMM procedure produces an estimated transitory risk with a size of $\hat\sigma^2_\epsilon = -cov(\Delta\hat e_{i,t}, \Delta\hat e_{i,t+1}) = -cov(\Delta e_{i,t} + \xi_{i,t}, \Delta e_{i,t+1} + \xi_{i,t+1}) = -\int cov(\Delta e_{i,t} + \xi_{i,t}, \Delta e_{i,t+1} + \xi_{i,t+1}) = \int \sigma^2_{i,\theta} + \sigma^2_{\xi,\theta}$, and an estimated permanent risk of $\hat\sigma^2_\psi = var(\Delta\hat e_{i,t}) - 2\hat\sigma^2_\theta = var(\Delta e_{i,t}) + (\sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta}) - 2\hat\sigma^2_\theta = \int var(\Delta e_{i,t}) + (\sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta}) - 2\hat\sigma^2_\theta = \int (\sigma^2_{i,\psi} + 2\sigma^2_{i,\theta}) + (\sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta}) - 2\hat\sigma^2_\theta = \int (\sigma^2_{i,\psi} + 2\sigma^2_{i,\theta}) + \sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta} - 2(\int \sigma^2_{i,\theta} + \sigma^2_{\xi,\theta}) = \int \sigma^2_{i,\psi} + \sigma^2_{\xi,\psi}$.

[30]Low et al. (2010), Davis and Von Wachter (2011).

**Figure 4:** Estimated Heterogeneity in PRs




Note: this figure plots the observed distribution of perceived income risks from SCE and the log-normal distribution estimation.

conomic models.[31] And similar to the approach with wage risks, the common practice in these models is to model the process of labor market transitions based on externally estimated stochastic process,[32]. This section shows that the survey-reported expectations of job separation/finding probabilities on average keep track with realized aggregate dynamics computed from the panel data, while masks a sizable degree of heterogeneity, which is not assumed in standard models.

For a fair comparison between perceptions and realizations which are regarding different horizons, I cast both probabilities into a continuous-time rate for a Poisson point process. Specifically, for the expectation, let the reported probability of separating from the current job in the next 12 months be $P_{i,t}(ue_{t+12}|e_t)$, then the corresponding monthly Poisson rate of job-separation $E_{i,t}(s_{t+1})$ is $-log(1 - P_{i,t}(u_{t+12}|e_t))/12$.[33] With the realized month-to-month flow rate estimated from CPS $P(ue_{t+1}|e_t)$ , the corresponding realized Poisson rate $s_{t+1}$ is $-log(1 - P(ue_{t+1}|e_t))$.

[31]For examples, see Krueger et al. (2016) and Bayer et al. (2019), etc.

[32]The exceptions are models endogenizing job search & match mechanisms, such as Ravn and Sterk (2017), Ravn and Sterk (2021), McKay (2017) in which typically job-separation rates remains exogenous and externally calibrated.

[33]This follows from the following mathematical fact: for a continuous-time Poisson process with an event rate of $\theta$, the arrival probability over a period of $\Delta t$ units of time is equal to $1 - exp^{-\theta\Delta t}$.

Figure 5 plots the converted job-separation/finding expectations and their respective realizations against each other. A few important patterns emerge. In addition, I plot the 25 and 75 percentile of the expectations across all survey respondents around its population average. A number of straightforward findings emerge. First, although the two series are independently constructed of each other, on average, perceptions did track the aggregate realizations relatively well. The most notable deviation between the belief and realization was during March 2020, which marked the unprecedented increase in the one-month job separation[34] and a dramatic decrease in job finding. Second, however, as shown by the wide 25/75 inter-range-percentile around mean expectations, individual respondents vastly disagree on their individual separation and finding probabilities. Since the question in the survey regards the individual-specific transitions, it is most reasonable to assume that this reflects the unobserved heterogeneity or information available to their individual status, which economists cannot directly observe.

## 4.5 Perceived income risk and consumption spending

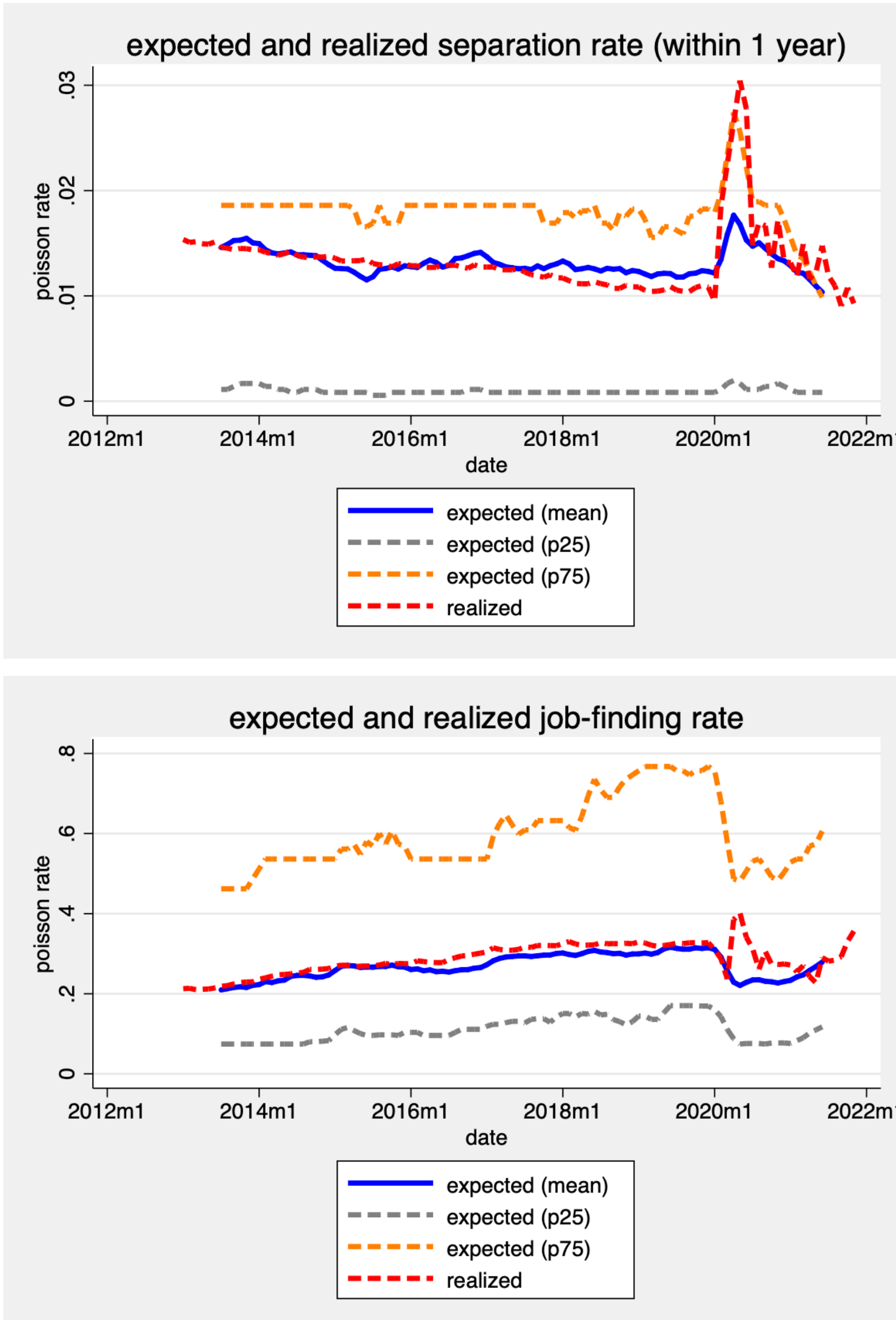
How do individual-specific perceived risks affect household economic spending decisions? One of the key testable predictions is that higher perceived risks should induce more precautionary saving motive, hence lowering current consumption, or increasing expected consumption growth. SCE directly surveys the self-reported spending plan, i.e. expected spending growth over the next year, which exactly corresponds to the object of our interest. [35] Therefore, we can evaluate if higher perceived risks translate affects spending plan consistently with precautionary saving motives.

In general, expected consumption growth with uncertain labor income does not have analytical expression with perceived income risks in it. This is because the optimal consumption paths crucially depends on the income process as well as the nature of this perceived income risks. But under

[34] The March observation was dropped in the graph, otherwise, it overshadows all other observations in the sample.

[35] Other work that directly examines the impacts of expectations on readiness to spend includes Bachmann et al. (2015) and Coibion et al. (2020). Related to this, there is a recent literature that relies on survey answers to measure marginal propensity to consume, such as Fuster et al. (2020) and Bunn et al. (2018).

**Figure 5:** Expected and Realized Job-separation/finding Rate




Note: realized job separation/finding rates are computed from CPS. Both are expressed as Poisson point rates in continuous time with one month as the unit of time. The 3-month moving average expected rate is plotted.

auxiliary assumptions, we could attain a close form expression of expected growth in consumption. Specifically, assume the agent maximizes discounted CRRA utility from consumption with discount rate $\theta$ and exogeously given interest factor $1 + r_t$, and the coefficient of relative risk aversion is $\rho$.

Under log normal income process, the expected consumption growth at time $t$ can be approximated as the following when the borrowing constraint is not binding. The expected consumption growth is higher if the borrowing constraint is binding at time $t$.

$$E_{i,t}(\Delta c_{i,t+1}) \approx \frac{1}{\rho}(r_t - \theta) + \frac{\rho}{2}\sigma^2_{i,t}(c_{i,t+1}) \tag{10}$$

The second term on the right above captures the effect from precautionary saving motive or possibly binding constraint. We could think of both as a consequence of market incompleteness(Parker and Preston, 2005). Regardless of the particular cause of consumption fluctuations, the term increases with the size of expected consumption risks. But we do not directly observe the expected variance of consumption of the individuals. So an additional assumption regarding the degree of insurance of consumption from income risks is necessary to link expected consumption risks to perceived income risks. The scenario of zero insurance or full pass-through, namely $\sigma^2_{i,t}(c_{i,t+1}) = var_{i,t}(\Delta y_{i,t+1})$, is most likely to happen when the income risks perceived by the agents are permanent. Under partial insurance, the consumption risks anticipated by the agents should be smaller than the perceived income risks. Let the partial pass-through parameter being $\kappa$, then the relationship between expected spending growth and perceived income risks can be written as the following.

$$E_{i,t}(\Delta c_{i,t+1}) \approx \frac{1}{\rho}(r_t - \theta) + \frac{\rho}{2}\kappa^2 var_{i,t}(\Delta y_{i,t+1}) \tag{11}$$

Since $\kappa \leq 1$, an OLS estimate coefficient of expected spending growth on perceived income risks reveals a lower bound of 1/2 of the size of relative risk aversion $\rho$. Table 1 reports the regression results of planned log spending growth over the next year on real and nominal perceived income risk in the variance terms[36]. Regardless of the specification, the perceived risk is indeed positively

[36]One common econometric concern with running regressions of this kind is the measurement error in the regressor, i.e. the perceived risks. In a typical OLS regression in which the regressor has i.i.d. measurement errors, the coefficient estimate for the imperfectly measured regressor has a bias toward zero. For this reason, if I find that

correlated with the expected spending growth as the precautionary saving motive would predict. Specifically, after controlling for individual fixed effect, i.e. discount rate, and time fixed effect i.e. interest rate, each unit increase in perceived variance leads to around a 3 percentage points increase in expected spending growth. This implies an estimated risk aversion coefficient in the range of 6-7. Besides, the precautionary saving motives are weaker for real earning risks than the nominal, but the two are not significantly different from each other.

**Table 1:** Perceived Income Risks and Household Spending Plan

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| perceived earning risk | 8.394*** | 8.399*** | 3.642*** | 3.243*** | | |
| | (1.175) | (1.176) | (0.533) | (0.537) | | |
| perceived earning risk (nominal) | | | | | 3.656*** | |
| | | | | | (0.990) | |
| perceived ue risk | | | | | | 0.353*** |
| | | | | | | (0.0553) |
| R-squared | 0.0010 | 0.00282 | 0.928 | 0.928 | 0.941 | 0.633 |
| Sample Size | 53178 | 53178 | 53178 | 53178 | 54584 | 6269 |
| Time FE | No | Yes | No | Yes | Yes | No |
| Individual FE | Yes | No | Yes | Yes | Yes | Yes |

Standard errors are clustered by household. *** p<0.001, ** p<0.01 and * p<0.05.

This table reports regression results of expected spending growth on perceived income risks (incvar for nominal, rincvar for real).

# 5 Perceived risks and wealth inequality

## 5.1 An overlapping generation model

I set up a standard incomplete market/life-cycle/general-equilibrium model without aggregate risks. The model structure resembles that of Huggett (1996), although it embeds a more realistic income risk profile and economic environment a la Carroll and Samwick (1997), Krueger et al. (2016) and Carroll et al. (2017).

expected spending growth is indeed positively correlated with perceived risks, taking into account the bias, it implies that the correlation of the two is greater in size.

In each period, a continuum of agents is born. Each agent $i$ lives for $L$ and works for $T$ ($T \leq L$) periods since entering the labor market, during which he/she earns stochastic labor income $y_\tau$ at the work-age of $\tau$. After retiring at age of $T$, the agent lives for another $L-T$ periods of life and receive social security benefits. We assume away aggregate risks in the benchmark model, therefore there is no need to treat calendar time $t$ from working age $\tau$ as two separate state variables, hence we suppress time script $t$. All shocks are idiosyncratic, or to put it differently, specific to the individual $i$.

### 5.1.1 Consumer's problem

The consumer chooses the whole future consumption path to maximize expected life-long utility, under a discount factor $\beta$ and constant survival probability $(1-D)$.

$$\max \quad \mathbb{E}\left[\sum_{\tau=0}^{\tau=L-1}(1-D)^\tau \beta^\tau u(c_{i,\tau})\right] \tag{12}$$

where $c_{i,\tau}$ represents consumption at the work-age of $\tau$. The felicity function $u(c)$ takes a standard CRRA form with relative risk aversion of $\rho$: $u(c) = \frac{c^{1-\rho}}{1-\rho}$. [37]

Denote total cash in hand at the beginning of the period $\tau$ as $m_{i,\tau}$, the end-of-period saving in period $\tau$ after consumption as $a_{i,\tau}$, the bank balance in period $\tau$ as $b_{i,\tau}$. Labor income $y_\tau$ is taxed at an income rate of $\lambda$ and social tax rate $\lambda_{SS}$. Also, assume $R$ is the gross real interest factor. The consumer starts with some positive bank balance in the first period of life, $b_1$, which may partly come from a lump-sum accidental bequest from the deceased population each period. The household makes consumption and saving decisions subject to the following intertemporal budget constraint.

[37] There is are bequest motive and preference-shifter along life cycle, but these features can be easily incorporated.

$$
\begin{aligned}
&a_{i,\tau} = m_{i,\tau} - c_{i,\tau} \\
&b_{i,\tau+1} = a_{i,\tau} R \\
&m_{i,\tau+1} = b_{i,\tau+1} + (1-\lambda)(1-\lambda_{SS}) y_{i,\tau+1} \\
&a_{i,\tau} \geq 0
\end{aligned}
\tag{13}
$$

In addition, I impose an external zero borrowing constraint. Without the external borrowing constraint, the agent will still self-imposed a lower bound for $\underline{a_\tau}$ to avoid the extremely painful zero consumption next period in the case of the worst draw of income shocks.

### 5.1.2 Income process

Each agent receives stochastic labor income during working age from $\tau = 0$ to $\tau = T$ and receives social security benefit after retirement. The income processes in both sub-periods can be defined in a generic manner as described below. In particular, it is assumed to follow a slight variant of the standard permanent/transitory income process used in the literature[38] by allowing the possibility of persistent unemployment risks. Specifically, $y_{i,\tau}$ is a multiplication of idiosyncratic labor productivity $n_{i,\tau}$ and the economy-wide wage rate $W$. The former consists of one permanent component $p_{i,\tau}$ and one potentially persistent or transitory $\xi_{i,\tau}$. The aggregate wage is to be determined by the general equilibrium. [39]

$$
\begin{aligned}
y_{i,\tau} &= n_{i,\tau} W \\
n_{i,\tau} &= p_{i,\tau} \xi_{i,\tau}
\end{aligned}
\tag{14}
$$

[38] Carroll et al. (2017), Kaplan and Violante (2018), etc.

[39] In the presence of aggregate risk, we need to allow $W$ being time-varying and this also means we need to be explicit about the difference between the calendar year and working age.

During the work, the permanent income component is subject to a mean-one white-noise shock $\psi$ in each period and grows according to a deterministic life-cycle profile governed by $G_\tau$, which usually follows a hump-shape according to existing estimates. (Gourinchas and Parker, 2002)

$$\begin{aligned} & p_{i,\tau} = G_\tau p_{i,\tau-1}\psi_{i,\tau} \\ & log(\psi_{i,\tau}) \sim N(-\frac{\sigma^2_\psi}{2}, \sigma^2_\psi) \quad \forall \tau \leq T \end{aligned} \tag{15}$$

The persistent/transitory shock $\xi_{i,\tau}$ takes different values depending on the transitory or persistent state of unemployment following a Markov process.[40]

$$\begin{aligned} & \xi_{i,\tau} = \begin{cases} \theta_{i,\tau} & \text{if} \quad \nu_{i,\tau} = e \quad \& \quad \tau \leq T \\ \zeta & \text{if} \quad \nu_{i,\tau} = u \quad \& \quad \tau \leq T \\ \mathbb{S} & \text{if} \quad \tau > T \end{cases} \\ & log(\theta_{i,\tau}) \sim N(-\frac{\sigma^2_\theta}{2}, \sigma^2_\theta) \end{aligned} \tag{16}$$

where $\zeta$ is the replacement ratio of the unemployment insurance and $\theta_{i,\tau}$ is the i.i.d. mean-one white noise shock to the transitory component of the income conditional on staying employed. Notice that the process above also embodies the income process after retirement after $\tau = T$. The agent receives social security with replacement ratio $\mathbb{S}$ and proportional to her permanent income and aggregate wage rate. Therefore, the effective pension benefit received is $\mathbb{S}p_{i,\tau}W$. I assume that the permanent income component after retirement just follows the determinist path without additional stochastic shocks.

During work age of any individual $i$, the transition matrix between unemployment ($\nu_{i,\tau} = u$) and employment ($\nu_{i,\tau} = e$) is the following.

[40]This formulation follows Krueger et al. (2016).

$$\pi(\nu_{\tau+1}|\nu_\tau) = \begin{bmatrix} \mho & 1-\mho \\ 1-E & E \end{bmatrix} \tag{17}$$

In general, this assumption implies some degree of the persistence of unemployment risks, but it conveniently nests the special case where the unemployment risk is purely transitory when $\mho = 1-E$, meaning the probability of unemployment is not dependent on the current status.

Unemployment risks are idiosyncratic, hence by the law of large numbers, the fraction of the population being unemployed and employed at each age, denoted by $\Pi^{\mho}_\tau$ and $\Pi^{E}_\tau$, respectively, are essentially deterministic and does not depend on age.

Notice that in the benchmark model laid out here, I assume the all parameters of income risks $\sigma_\psi$, $\sigma_\theta$, $\mho$, and $E$ to be age-invariant (equivalent to time-independent in this setting). By doing this, I avoid making explicit assumptions on the stochastic process of income risks. This is a common practice in the incomplete market macro literature since Gourinchas and Parker (2002) and Cagetti (2003). It is also not fundamentally different from assuming a deterministic age-specific risk profile, as in some variants of the models with the life-cycle component.[41] I allow for income risks to be stochastic/state-dependent in one of the extensions of the model discussed later, in Appendix A.11.

### 5.1.3 Value function and consumption policy

The following value function characterizes the consumer's problem.

$$V_\tau(\nu_{i,\tau}, m_{i,\tau}, p_{i,\tau}) = \max_{\{c_{i,\tau}, a_{i,\tau}\}} \quad u(c_{i,\tau}) + (1-D)\beta \mathbb{E}_\tau \left[V_{\tau+1}(\nu_{i,\tau}, m_{i,\tau+1}, p_{i,\tau+1})\right] \tag{18}$$

where the three state variables for the agents are current employment status $\nu_{i,\tau}$, total cash in hand $m_{i,\tau}$ and permanent income $p_{i,\tau}$. $\nu_{i,\tau}$ drops from the state variables in the special case of

[41]See Carroll et al. (2017) and other examples.

purely transitory unemployment shock ($\mho = 1 - E$).[42]

The solution to the problem above is the age-specific optimal consumption policies $c^*_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau})$ and saving policies $a^*_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau})$ both as a function of all state variables.

### 5.1.4 Technology

The economy has a standard CRS technology that turns the capital and supplied efficient units of labor into aggregate output.

$$Y = ZK^\alpha N^{1-\alpha} \tag{19}$$

The capital depreciates at a rate of $\delta$ each period.

The factors of input markets are fully competitive. Euler Theorem implies that the output either becomes labor income or capital income.

### 5.1.5 Demographics

For simplicity, we assume there is no population growth. With a deterministic life-cycle profile of survival probabilities, there exists a stable age distribution $\{\mu_\tau\}_{\mu=1,2,..L}$ such that $\mu_{\tau+1} = (1-D)\mu_\tau$ and $\sum_{\tau=1}^{L} \mu_\tau = 1$. The former condition reflects the probability of survivals at each age and the latter is a normalization that guarantees the fraction of all age groups sum up to 1.[43]

---

[42] Another trick used in the literature to reduce the number of state variables is to normalize the value function by permanent income level $p_\tau$, so that it drops from the state variable. I also use endogenous grid method (EGM) by Carroll (2006).See Appendix for the detailed solution algorithm.

[43] In a more general setting with a constant population growth rate $n$ and age-specific survival probability $1 - D_\tau$, the condition becomes $\mu_{\tau+1} = \frac{(1-D_{\tau+1})}{1+n}\mu_\tau \quad \forall \tau = 1, 2...L$, as discussed in Ríos-Rull (1996) and Huggett (1996).

### 5.1.6 Government

Government runs a balanced budget in each period. Therefore, outlays from unemployment insurances are financed by the income tax that is levied on both labor income and unemployment benefit. Given a replacement ratio $\zeta$, and the proportion of employed population, the corresponding tax rate $\lambda$ can be easily pinned down based on the equation below. [44]

$$\lambda \left[1 - \Pi^{\mho} + \zeta \Pi^{\mho}\right] = \zeta \Pi^{\mho} \tag{20}$$

Social security tax rate $\lambda_{SS}$ is also determined in the model depending on the pension replacement ratio $\mathbb{S}$, the permanent income ratio and the relative population size of the retired and the working age, and the aggregate employment rate.

$$\lambda_{SS} \sum_{\tau=1}^{T} G_\tau (1 - \Pi^{\mho}) = \mathbb{S} \sum_{\tau=T+1}^{L} G_\tau \tag{21}$$

### 5.1.7 Stationary equilibrium

Denote $x = \{m, p, \nu\} \in X$ as the idiosyncratic state of individuals. At any point in time, agents in the economy differ in age $\tau$ and their idiosyncratic state $x$. The former is given by $\{\mu_\tau\}_{\mu=1,2,..L}$. For the latter, using $\psi_\tau(B)$ to represent the fraction of agents at age $\tau$ whose individual states lie in $B$ as a proportion of all age $\tau$ agents. ($B$ is essentially a subset of Borel $\sigma$-algebra on state space $X$.) The distribution of age $\tau = 1$ agents depend on the initial condition of labor income outcomes and the size of accidental bequests, if any. For any other age $\tau = 2...L$, the distribution $\phi_\tau(B)$ evolves as the following.

[44] This convenient result crucially depends on the assumption that unemployment insurance benefit is paid proportionally to permanent income.

$$\psi_\tau(B) = \int_{x\in X} P(x, \tau-1, B)\mathrm{d}\psi_{\tau-1} \quad \text{for all} \quad B \in B(X) \tag{22}$$

where $P(x, \tau-1, B)$ is the probability for an agent to transit to $B$ in the next period, conditional on the individual state $x$ at age $\tau - 1$. It depends on the optimal consumption policy $c^*(x, \tau)$ at age $\tau$ and the exogenous transition probabilities of income shocks.

In the absence of the aggregate risk, I focus on the stationary equilibrium of the economy (StE) which consists of consumption and saving policies $c(x, \tau), a(x, \tau)$, constant production factor prices, including real interest rate $R$ and the wage $W$, the initial wealth of newborn $b_1$, unemployment benefit $\zeta$, tax rate $\lambda$ and the time-invariant distribution $(\psi_1, \psi_2, \ldots, \psi_L)$ such that

1. Consumption and saving policies are optimal given the real interest rate $R$, wage $W$, the tax rate $\lambda$.

$$c(x, \tau) = c^*(x, \tau)$$

$$a(x, \tau) = a^*(x, \tau)$$

2. Distributions $(\psi_1, \psi_2, \ldots, \psi_L)$ are consistent with optimizing behaviors of household, as described in Equation 22.

3. The factor markets are clearing.

$$\begin{gathered}\sum_\tau \mu_\tau \int_X a(x, \tau)\mathrm{d}\psi_\tau = K \\ \sum_{\tau=0}^{T-1} \mu_\tau \Pi_\tau^E = N\end{gathered} \tag{23}$$

4. Firm optimization under competitive factor markets.

$$W = Z(1-\alpha)(K/N)^\alpha$$

$$R = 1 + Z\alpha(K/N)^{\alpha-1} - \delta$$

5. Initial bank balance equal to accidental bequests.

$$b_1 = \sum_{\tau} \mu_\tau D \int_{x\in X} a(x,\tau) R \mathrm{d}\psi_\tau$$

6. Government budget is balanced as described in Equation 20 and 21.

The economy may potentially arrive at different stationary equilibrium depending on the specific assumptions about objective or subjective models under the configurations.

## 5.2 Calibration

The central inputs of the model in this paper, the size and the heterogeneity in perceived income risks, are estimated from the survey, using the auxiliary model laid out in Section 4.3. Here, I discuss other model parameters in great details.

**Life-cycle** The model is set at yearly frequency. The working age spans from 25 years old to 65 years old ($T = 40$) and the agent dies with certainty at age of 85 ($L = 60$). The constant death probability before the terminal age is set to be $D = 0.625\%$.

As to the deterministic permanent income profile over the life-cycle, $G_\tau$, I draw on an age polynomial regressions of the earning growth from SIPP for workers aged between 25-65, controlling for other observable demographic variables such as education, gender, occupation, and time fixed effects, etc. This produces very similar estimation results to that in Gourinchas and Parker (2002), Cagetti (2003) and Kaplan and Violante (2014). The estimated income profile is plotted in Appendix A.12. For the retirement phase, I assume a one-time drop of 20% in permanent income in the age of 66, i.e. $G_{41} = 0.8$, and then the permanent income stays flat till death. This produces an average expected growth rate of permanent income over the entire life-cycle exactly equal to one. This serves as a normalization. Note that although alternative assumptions, such as a more smooth decline of income after retirement, do change the wealth distribution across generations among the retired, they do not change the consumption/saving decisions as such a profile is entirely deterministic.

**Initial conditions** Assumptions about cross-sectional distribution of the initial permanent productivity and liquid asset holdings matter for the subsequent wealthy inequality. I set the standard deviation of the log-normally distributed initial permanent individual productivity $p_{i,\tau}$ to be 0.6 to match the earning heterogeneity in "usual income" (approximated permanent income) at age 25 from the SCF. Initial liquid assets holdings at $\tau = 0$ is assumed to have a cross-sectional standard-deviation of 0.50.

**Income risks** Given the critical importance of the income risks assumption in my model, In addition to my estimates from SIPP, as reported in Table A.6, I thoroughly survey the parameters used in the existing incomplete market macro literature, as summarized in Table A.7 in the Appendix. For comparison, I convert all risks into the annual frequency (although the model is set quarterly). Whenever group-specific risks are assumed, i.e. depending on the education and age, I summarize it as a range. Also, for those models which assume a persistent instead of permanent income risk component, I treat their assumed size of the persistent risks as a lower bound for the permanent risk. (One can think of the permanent income shock as a limiting case of AR(1) shock, with the persistence parameter infinitely close to 1. The effective income risks increase with the persistence of the shock.) For models with income risks dependent on aggregate business cycles a la Krusell and Smith (1998), I compute the steady-state size of idiosyncratic risks using the transition probabilities of the aggregate economy used in the paper.

Despite the disagreements in these estimates or model inputs, the earning risks used in these models are constantly larger than those perceived reported in the survey. Meanwhile, the perceived risk of unemployment is higher in the survey than in these models and the perceived employment probability is lower in the survey than in these models. I use the median values of each parameter in the literature as the objective income risks profile $\Gamma$. In particular, in our baseline calculation, I set $\sigma_\psi = 0.15$ and $\sigma_\theta = 0.10$. The yearly probability of staying on unemployment is $\mho = 0.18$ and that of staying employed $E = 0.96$, as used in Krueger et al. (2016).

**Technology** The annual depreciation rate is set to be $\delta = 2.5\%$. The capital share takes a standard value of $\alpha = 0.36$, for the U.S. economy. Without aggregate shocks, $Z$ is simply a normalizer. Therefore, I set its value such that the aggregate wage rate $W$ is equal to one under a capital/output ratio $K/Y = 3$ at the steady-state level of employment in the model.

**Government policies** Unemployment insurance replacement ratio is set to be $\mu = 0.15$, as the same as Krueger et al. (2016). The pension income relative to the permanent income is assumed to be $\mathbb{S} = 60\%$. This, plus the 20% drop in permanent income, gives an effective deterministic income drop of 48% from the working-age to retirement, which corresponds to an empirical replacement ratio estimated for the U.S. economy. The corresponding tax rates financing the unemployment insurance and social security is determined in the equilibrium within the model.

**Preference** The discount factor is set to be $\beta = 0.98$, the average value estimated in the models with heterogeneous time preferences such as Carroll et al. (2017), Krueger et al. (2016). The coefficient of relative risk aversion $\rho = 2.0$, which is common in this literature.

Table 2 summarizes the parameters used in this calibration.

# 6 Model results (preliminary)

## 6.1 Baseline model

I first examine the wealth accumulation and wealthy inequality generated from a benchmark calibration identical to that used in Krueger et al. (2016); Carroll et al. (2017). In particular, I use the standard parameterization on permanent and transitory risks at the annual frequency being $\sigma_\psi = 0.15$ and $\sigma_\theta = 0.15$, and the unemployment risks $U2U = 0.18$ and $E2E = 0.96$, a median size of income risks from the existing literature summarized in Table A.7. The baseline of Figure 6

**Table 2:** Model parameters

| block | parameter name | values | source |
|---|---|---|---|
| risk | $\sigma_{\psi}$ | 0.15 | Median estimates from the literature |
| risk | $\sigma_{\theta}$ | 0.15 | Median estimates from the literature |
| risk | $U2U$ | 0.18 | Median estimates from the literature |
| risk | $E2E$ | 0.96 | Median estimates from the literature |
| initial condition | $\sigma_{\psi}^{\text{init}}$ | 0.629 | Estimated for age 25 in the 2016 SCF |
| initial condition | bequest ratio | 0 | assumption |
| life cycle | $T$ | 40 | standard assumption |
| life cycle | $L$ | 60 | standard assumption |
| life cycle | $1 - D$ | 0.994 | standard assumption |
| preference | $\rho$ | 1 | standard assumption |
| preference | $\beta$ | 0.98 | standard assumption |
| policy | $\mathbb{S}$ | 0.65 | U.S. average |
| policy | $\lambda$ | N/A | endogenously determined |
| policy | $\lambda_{SS}$ | N/A | endogenously determined |
| policy | $\mu$ | 0.15 | U.S. average |
| production | $W$ | 1 | target values in steady state |
| production | K2Y ratio | 3 | target values in steady state |
| production | $\alpha$ | 0.33 | standard assumption |
| production | $\delta$ | 0.025 | standard assumption |

This table reports parameters used in the benchmark objective model. All parameters, whenever relevant, are at the annual frequency.

reproduces the well-known result[45] that a carefully calibrated standard one-asset incomplete market model without additional heterogeneity such as that in time discount rates imply less wealth inequality (a Gini coefficient of 0.65 in partial equilibrium and 0.64 in general equilibrium) than that in the data, which is measured by either total net wealth from the 2016 vintage of SCF (a Gini coefficient of 0.85), or net liquid wealth as defined in Kaplan et al. (2014) (a Gini coefficient of 0.92).

The life-cycle profile of wealth is another dimension of the model implications that can be compared to its data counterparts. The baseline in the bottom panel of Figure 6 plots the hump-shaped average wealth over the life cycle implied by the model against the median net liquid wealth between the age of 25 to 85 from SCF. The model-implied wealth accumulation over the working age resembles the data rather well. At the same time, the baseline model predicts the share of hands-

[45] For a thorough survey on this topic, see Guvenen (2011), De Nardi (2015), and Kaplan and Violante (2018).

to-month households (H2M)[46] of 0.09, significantly lower than 0.31, the share computed based on net liquid wealth in SCF. This reproduces the second discrepancy between the model and data.

One major divergence between the model and the data has to do with the high savings of the old seen in the data, in comparison with the sharp decline in wealth toward zero in the model, as the latter dictates it is optimal to consume all wealth at the end of the life. Such a divergent pattern is usually accounted for by specifically taking into account the bequest motives in the literature.[47] As the focus of this paper is on labor income risks of the work-age, I choose not to model such a mechanism.

There are two general-equilibrium (GE) mechanisms at play in the model. (1) GE allows for the endogenous determination of real interest rate via the asset markets clearing; (2) GE lets the resource constraints imposed by balancing the government budget determine social security tax and the tax rate used to finance unemployment insurance. Allowing for GE mechanisms lead to two notable differences between partial equilibrium (PE) and GE. First, wealth inequality measured by Gini coefficient is lower in GE (0.64) than PE (0.67). Second, GE forces contribute to a steeper build-up of the buffer stock savings by the young households. This is primarily due to a higher return to savings in GE than in PE.

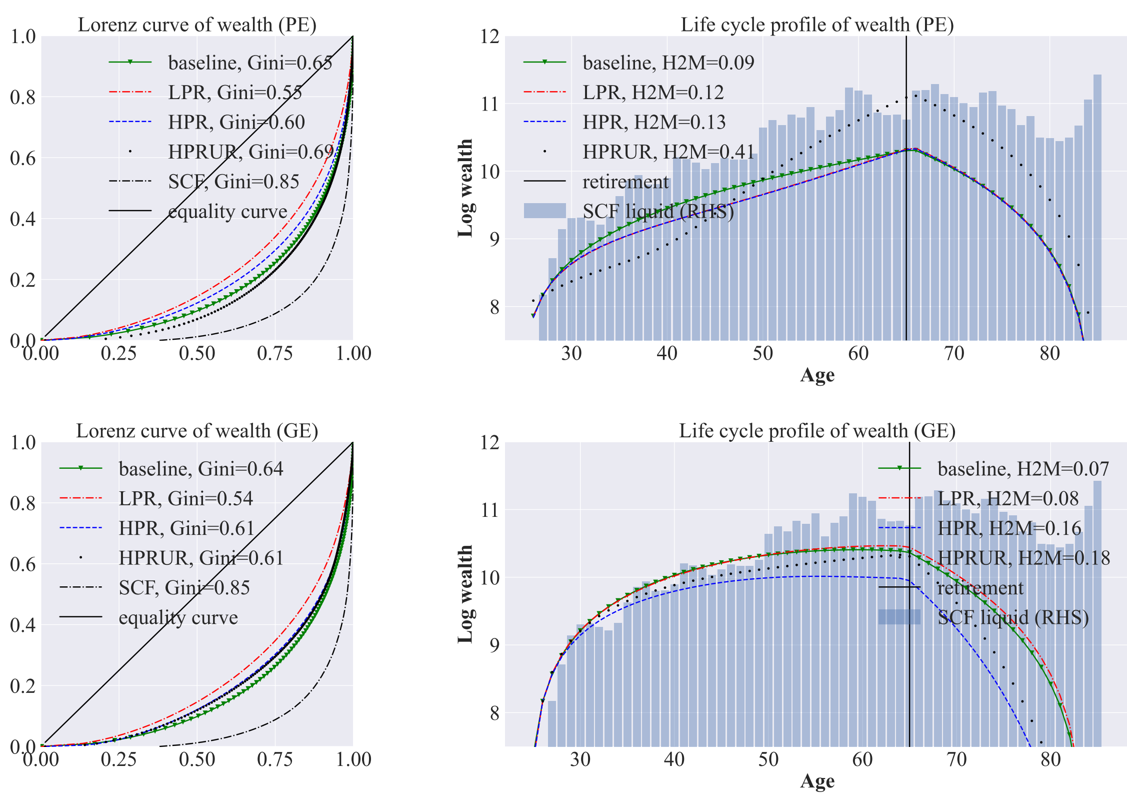
## 6.2 Model results with survey-implied risks

This section sequentially explores how directly incorporating the size and the heterogeneity of the survey-implied income risks in the same model jointly accounts for a fraction of the discrepancies between the baseline model prediction and the observed data. First, an average lower wage risk ($LPR$). Second, heterogeneous perceived wage risks in addition to the average lower size ($HPR$). Third, heterogeneous unemployment risks ($HPRUR$), as revealed in perceived U2U and E2E probabilities. Fourth, in addition to heterogeneous risks, I also allow for heterogeneous growth rates

[46]The H2Ms are defined as agents whose wealth to permanent income ratio is below 0.5.
[47]De Nardi (2004).

of wage ($HPRURG$). Finally, I allow for time preference heterogeneity in addition to perceived income risks ($HPRURGTP$).

**Figure 6:** Wealth Inequality in Partial and General Equilibrium: A Model Comparison




Note: the panel shows, under various model assumptions, the Lorenz curve of households wealth (left) and the model-generated life-cycle profile of log average wealth compared to the average net liquid wealth by age in the 2016 vintage of Survey of Consumer Finance (SCF) (right) in the partial equilibrium (upper panel) and in general equilibrium (bottom panel).

### 6.2.1 Lower wage risks (LPR)

For LPR calibration, I keep everything the same as baseline calibration above, except for setting the permanent and transitory risks to be smaller based on an upper bound of total perceived risk of 0.04, i.e. $\sigma_{\psi} = 0.03$ and $\sigma_{\theta} = 0.02$.

The LPR in Figure 6 confirms the two straightforward implications of a smaller size of risks. First, a lower PR induce less precautionary saving motive and reduces buffer-stock savings of all working agents, as indicated by a lower line of the wealth before retirement than the benchmark model. This generates a higher fraction of "hands-to-mounth"(H2M) agents (0.13 in PE) compared to 0.09 in the baseline model.

Second, a lower PR unambiguously leads to *less* wealth inequality than in the benchmark model, as shown in the Lorenz curve in Figure 6. Lower income risks result in less ex-post dispersion in uninsured income shocks, while the ex-ante precautionary saving motives do not differ across agents. Therefore, in order to reconcile the observed wealth inequality with lower perceived wage risks, admitting additional heterogeneity in income risks is critical.

### 6.2.2 Heterogeneous wage risks (HPR)

As shown in Section 4.1, a large degree of heterogeneity in PRs is attributable to individual fixed effects, which might reflect the true ex-ante heterogeneity in wage risks facing different individuals beyond common observable factors. Hence, I directly calibrate the wage risks using the estimated distribution of PRs and the size of unobserved heterogeneity, estimated in Section 4.3.

I use three equally probable values $[0.01, 0.02, 0.04]$ for $\sigma_\psi$ and $\sigma_\theta$, which are discretized from the estimated log-normal distribution of $PRs$ to calibrate such heterogeneity. Allowing heterogeneity in PRs in addition to a lower average risk creates two counterbalancing forces. Although on one hand, heterogeneity in risks unambiguously contributes to more wealth inequality, as it induces different precautionary saving motives and buffer stock savings, such a force was counteracted by the average lower risks as the latter objectively induces less income and wealth inequality, as shown in $LPR$. Therefore, although the PE Gini coefficient increase from 0.55 in $LPR$ to 0.6 in $HPR$, and the GE Gini coefficient increases from 0.54 to 0.61, both remain lower than in the baseline model. At the same time, the fraction of H2M agents remain larger than in the baseline model. This suggests that incorporating heterogeneity narrowly in wage risks probably misses out an important source of heterogeneity, that of unemployment risks.

### 6.2.3 Heterogeneous unemployment risks (HPRUR)

A standard incomplete market model with unemployment spells typically parameterizes the model with one homogenous pair of $U2U$ ($\mho$ in the model) and $E2E$ ($E$ in the model) probabilities (for instance, Krueger et al. (2016)). But this may mask the unobserved heterogeneity among agents and their true perceived unemployment risks given the information they have about their own idiosyncratic circumstances (Mueller and Spinnewijn (2021)).

In order to capture the heterogeneity in unemployment risks, I adopt the same approach as for perceived wage risks in Section 4.3 to fit a truncated log normal distribution to the survey-reported perceived U2U and E2E probabilities. (See Figure A.14). The estimated distribution is further discretized into three equally probable grid points $[0, 0.02, 0.24]$ of $U2U$ and $[0.96, 0.99, 1.0]$ of $E2E$. The resulting model with both heterogeneous wage risks and unemployment risks ($HPRUR$) generates a higher degree of wealth inequality (a Gini coefficient of 0.69 in PE) compared to the baseline model (a Gini coefficient of 0.65). In addition, the fraction of H2M further increases from 0.13 to 0.41 in PE and from 0.16 to 0.18 in GE.

What's particularly noteworthy is that the $HPRUR$ produces a steeper life-cycle profile of wealth compared to both the baseline model and LPR which resembles the SCF profile better.

### 6.2.4 Heterogeneous growth rates (HPRURG)

Despite the main theme of this paper is the heterogeneity in income risks, the density forecasts also provide individual specific expected wage growths which exhibit substantial heterogeneity, a standard deviation across respondents of 0.03, or 3 percentage points in annual growth rates. (See Figure A.14) I further extend the $HPRUR$ model above to incorporate such heterogeneity. In particular, I let the heterogeneity in the 1-year-ahead wage growth forecast be translated into three equal probable distinctive deterministic wage profiles, as plotted in Figure A.13. This essentially makes the assumption that the heterogeneity in wage growth from one year to another completely reflects perceived differences in the permanent component of the wage growth.

As shown in Table 3, the implied wealth Gini from allowing heterogeneous growth rates ($HPRURG$), not surprisingly, increases further from 0.69 to 0.72 in PE. Furthermore, the fraction of H2M are closer to those in SCF regardless of the cutoff values of wealth-to-permanent-income ratio.

**Table 3:** Summary of models results and data

| | Model/Data | Gini coeff | H2M share (0.1) | H2M share (0.3) | H2M share (0.5) |
|---|---|---|---|---|---|
| 0 | SCF (liquid) | 0.85 | 0.18 | 0.26 | 0.31 |
| 1 | baseline (PE) | 0.65 | 0.02 | 0.04 | 0.09 |
| 2 | LPR (PE) | 0.55 | 0.02 | 0.06 | 0.12 |
| 3 | HPR (PE) | 0.60 | 0.03 | 0.07 | 0.13 |
| 4 | HPRUR (PE) | 0.69 | 0.17 | 0.28 | 0.41 |
| 5 | HPRURG (PE) | 0.72 | 0.17 | 0.29 | 0.43 |
| 6 | HPRURGTP (PE) | 0.78 | 0.36 | 0.58 | 0.68 |
| 7 | baseline (GE) | 0.64 | 0.02 | 0.05 | 0.07 |
| 8 | LPR (GE) | 0.54 | 0.02 | 0.05 | 0.08 |
| 9 | HPR (GE) | 0.61 | 0.08 | 0.13 | 0.16 |
| 10 | HPRUR (GE) | 0.61 | 0.07 | 0.13 | 0.18 |
| 11 | HPRURG (GE) | 0.63 | 0.08 | 0.13 | 0.16 |
| 12 | HPRURGTP (GE) | 0.65 | 0.15 | 0.20 | 0.26 |

This table reports the model-implied Gini coefficient and shares of hands-to-mouth agents, whose wealth to permanent income ratio are below 0.1, 0.3, 0.5, respectively, in both PE and GE. The same statistics in the data are computed using 2016 SCF.

### 6.2.5 Heterogeneous time preferences (HPRURGTP)

One of the most common additional features to the baseline model in the existing literature to account for wealth inequality is to preference heterogeneity in time preference ($\beta$) in the model) (Krusell and Smith (1998), Krueger et al. (2016), Carroll et al. (2017).) Such an assumption was later supported by some empirical evidence and laboratory experiments. [48] However, in spite of such indirect evidence, as the exact degree of time preference heterogeneity in the model cannot be directly observed and estimated, the authors commonly adopt the "revealed preference" approach to indirectly infer the model-implied heterogeneity in preferences.

[48] For instance, Epper et al. (2020) directly elicited time preferences of individuals via experiments and show that they have real effects on wealth accumulation.

Compared to such an approach, this paper argues that survey-implied heterogeneity has the advantage of being directly observable and useful in the model. Hence, the heterogeneity of income risks and growth rates is another observable factor that should be first accounted for before attributing the unexplained wealth inequality to solely preference heterogeneity. Another advantage, although not explored in this paper, is that disciplining the model with observed heterogeneity such as in income risks perceived by agents makes it more transparent and clear to perform welfare analysis in these models, than that with unobserved preference heterogeneity.

If I allow the agents in the economy to be equally likely to be endowed with a time discount factor $\beta$ of $[0.9, 0.96, 0.98]$, the Gini coefficient further increased from 0.72 to 0.78 in PE, as shown by $HPRURGTP$ in Table 3. But in the meantime, bringing in time preference heterogeneity seems to make the share of H2M agents further deviate from that seen in the data in addition to the $HPRURG$ model. It suggests that time discount rate heterogeneity is not critical to explaining the low liquid assets holdings of H2M agents, if a lower size and heterogeneous income risks are directly calibrated in these model. However, preference heterogeneity remains necessary in accounting for overall wealth inequality.

## 6.3 Subjective perceived risks

So far, all the model experiments have maintained the assumption of full-information-rational-expectation. I do allow for heterogeneity in these risk parameters across agents, but it still treats the survey-implied risks of as the true model risk parameters that determine the dispersion of income shocks, as an alternative calibration to the conventional assumptions.

But it is critical to consider how robust the results are if we adopt a different assumption that agents' perceive risks as reported in the survey only shape their consumption/saving decisions (as calibrated $HPRUR$), but are somehow different from the true underlying risk parameters, which objectively govern the distribution of income shocks (as calibrated in the baseline model).

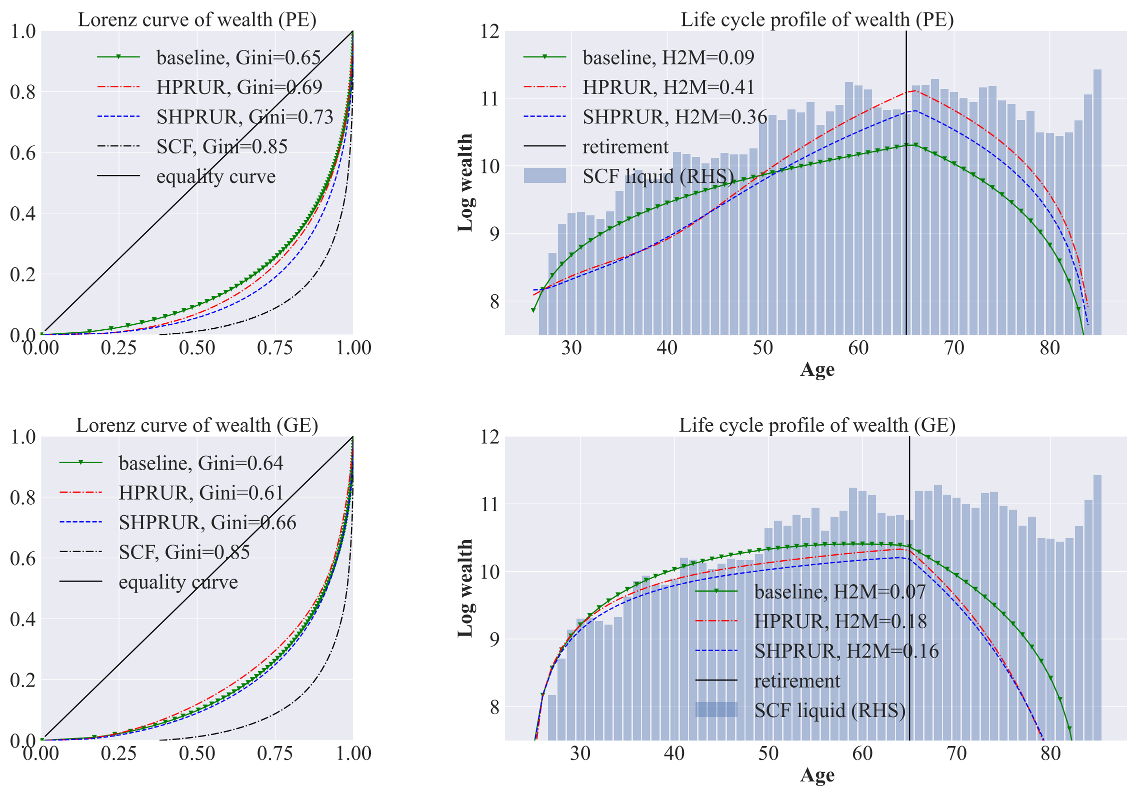
Such a model exercise is actually not just a robustness check, but also an experiment model that breaks down the model effects of heterogeneous and lower income risks on wealth inequality into two channels. The first channel can be called the "choice" channel, as it is via ex-ante consumption/saving decisions of the agents based on certain perceived income risks. The second channel can be called "outcome" channel, which is due to the ex-post realized dispersion of income shocks.

The key finding from exercise is that the additional wealth inequality from heterogenous income risks is driven by ex-ante "choice" channel, which is counteracted by the "outcome" channel, while the higher H2M share is a consequence of both ex-ante and ex-post mechanisms.

In particular, Figure 7 compare the subjective model $SHPRUR$ with both the baseline and $HPRUR$ model as calibrated above. Compared to the baseline model, the subjective model shifts the Lorenz curve further outward (A Gini of 0.73 in PE and 0.66 in GE), even more so than the objective model. Such a shift only comes from changes in ex-ante saving behaviors when a heterogenous and lower income risk profile is added to the baseline model. This suggests that even if we don't recalibrate the objective income risks in the baseline model but simply let the survey-implied risks be a better input in predicting consumption/saving choices, it contributes to the unexplained wealth inequality. At the same time, the fraction of H2M consumers implied by the subjective model (0.36 in PE) is smaller than the objective model (0.41 in PE), but is closer to that seen from data (0.31 in SCF).

The subjective model turns out to be more robust to the introduction of GE forces in the model. As shown in the bottom panel of Figure 7, even in GE, some of the wealth inequality and under-saving of agents are undone, but the subjective model still generates higher wealth inequality than the baseline model.

**Figure 7:** Wealth Inequality in Partial and General Equilibrium: Objective v.s. Subjective




Note: the panel shows, under objective ($HPRUR$) and subjective assumptions ($SHPRUR$), respectively, the Lorenz curve of households wealth (left) and the model-generated life-cycle profile of log average wealth compared to the average net liquid wealth by age in the 2016 vintage of Survey of Consumer Finance (SCF) (right) in the partial equilibrium (upper panel) and in general equilibrium (bottom panel).

# 7 Conclusion

A large class of incomplete-market macroeconomic models featuring realistic size of uninsured idiosyncratic income risks and wealth inequality has not incorporated one observable dimension of heterogeneity in income risks in these models. Utilizing the recently available large-scale survey data that elicits density forecasts of wage growth, I incorporate two main empirical patterns of income risk perceptions in these models: a lower perceived risk than conventional estimates and substantial heterogeneity beyond observable factors. The survey evidence indicates the possible "unobserved heterogeneity" or the "superior information" problem documented in the literature, confirming an upward bias in the assumed size of income risks in these models compared to what people report in surveys. Incorporating the survey-implied heterogeneity and lower perceived risks helps partly explain the low liquid asset holdings of a large fraction of households, the presence of many hands-to-mouth agents and an additional fraction of wealthy inequality.

As an additional exploration, I also extend the benchmark model to allow for subjective perceived risks to be different from the objective ones that drive the realized dispersion of the shocks, possibly due to behavioral bias. With such an extension of the model, I can explicitly break down the aggregate effects of idiosyncratic income risks into two components: one via ex-ante choices, i.e. the saving behaviors according to the perceived risks, and the other via ex post outcomes, i.e. the realized income inequality.

This paper also presents a demonstration of the rich possibility of incorporating survey data reflecting real-time heterogeneity in expectations/perceptions in heterogeneous-agent models. In a world with increasingly rich survey data that directly measures expectations, economists are no longer forced to make stringent assumption of rational expectations. Directly using survey-implied heterogeneity helps match empirical patterns of the macroeconomy.

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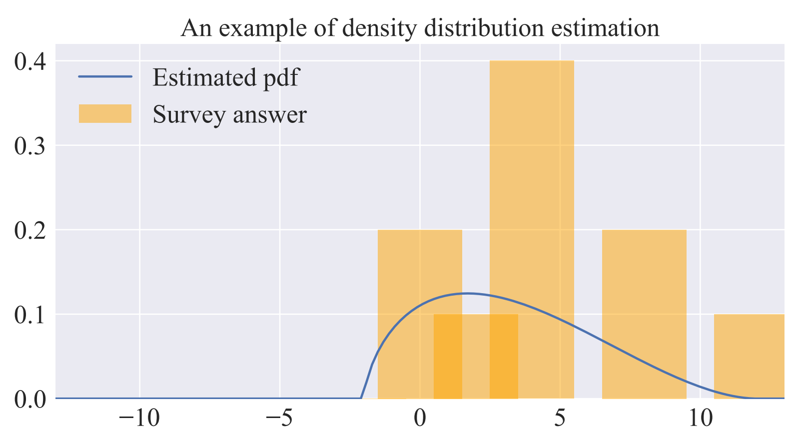
# A Online Appendix

## A.1 Density estimation of survey answers

With the histogram answers for each individual in hand, I follow Engelberg et al. (2009) to fit each of them with a parametric distribution accordingly for three following cases. (See Figure A.1 for an example.) In the first case, when there are three or more intervals filled with positive probabilities, it was fitted with a generalized beta distribution. In particular, if there is no open-ended bin on the left or right, then a two-parameter beta distribution is sufficient. If there is an open-ended bin with positive probability on either left or right, since the lower bound or upper bound of the support needs to be determined, a four-parameter beta distribution is estimated. In the second case, in which there are exactly two adjacent intervals with positive probabilities, it is fitted with an isosceles triangular distribution. In the third case, if there is only one positive-probability of interval only, i.e. equal to one, it is fitted with a uniform distribution.

**Figure A.1:** An illustration of the density estimation of the survey answer




Note: the figure plot one example of the bin-based forecast of wage growth at SCE and how it is fit by a parametric distribution. The horizontal axis is the values of expected wage growth and the vertical axis is the probability assigned by the respondent.

For all the moment's estimates, there are inevitably extreme values. This could be due to the idiosyncratic answers provided by the original respondent, or some non-convergence of the numerical estimation program. Therefore, for each moment of the analysis, I exclude top and bottom 1% observations, leading to a sample size of around 53,180.

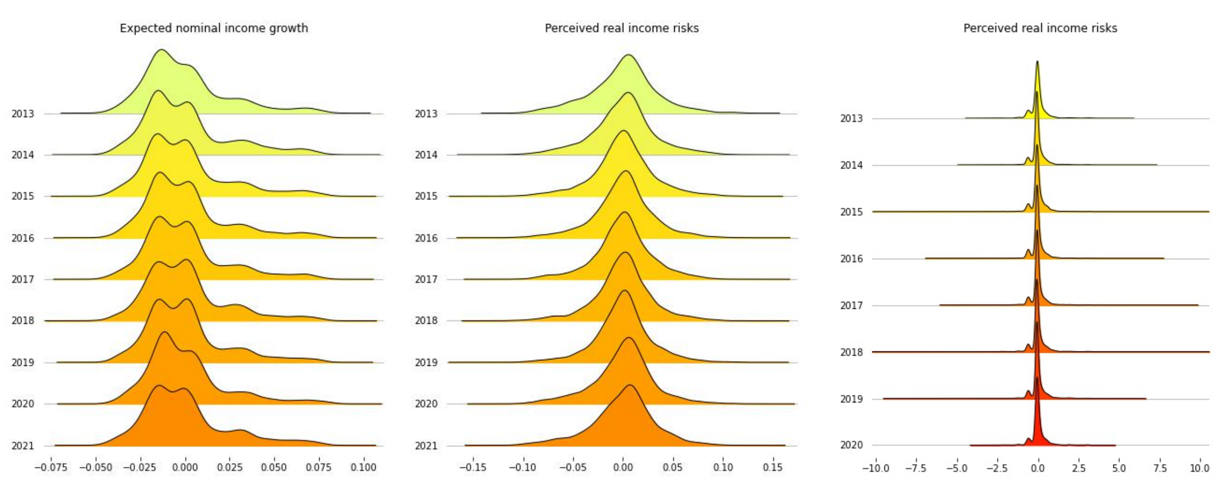
I also recognize what is really relevant to many economic decisions such as consumption is real income instead of nominal income. I use the inflation expectation to convert expected nominal earning growth to real growth expectations.

The real earning risk, namely the variance associated with real earning growth, if we treat inflation and nominal earning growth as two independent stochastic variables, is equal to the summed variance of the two. The independence assumption is admittedly an imperfect assumption because of the correlation of wage growth and inflation at the macro level. Therefore, throughout the paper, I also report results with nominal wage growth forecast directly.

## A.2 Other facts about PR

### A.2.1 Expected wage growth, and perceived skewness

**Figure A.2:** Dispersion in Unexplained Perceived Income Risks

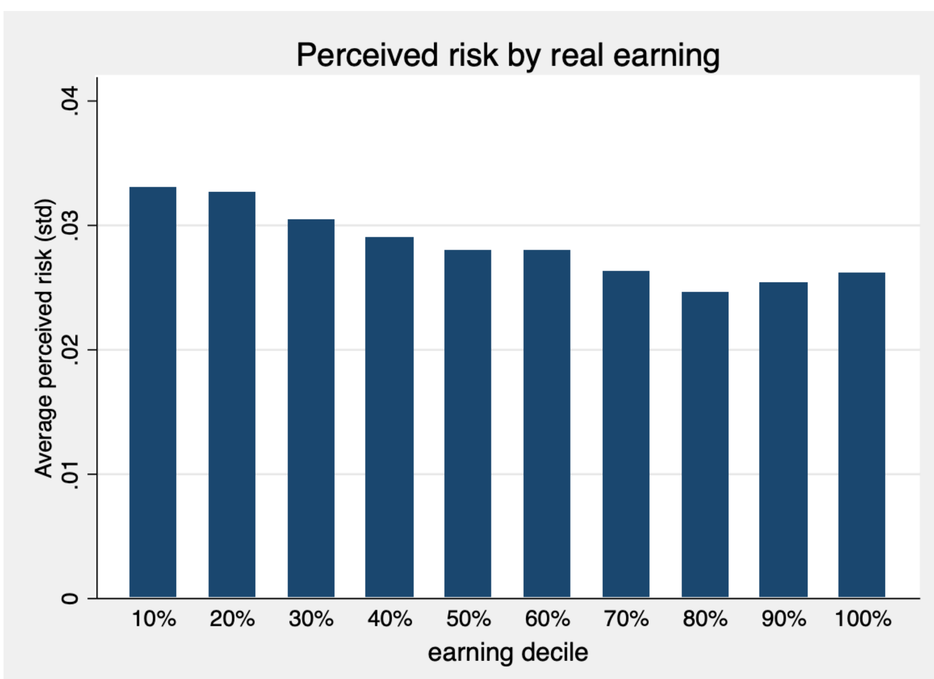



Note: this figure plots the distributions of expected nominal, real and perceived skewness of 1-year-ahead wage growth.

### A.2.2 PR by realized earnings

Standard models with idiosyncratic income risks do not assume heterogeneity by permanent income in addition to the observed group factors that may affect permanent income, such as education. Is it so in risk perceptions? It turns out that PR does correlate with the realized outcomes of the individuals. For a subsample of around 4000 observations, SCE surveys the annual earning of the respondent along with their risk perceptions. I group individuals into 10 groups based on their reported earning (within the same time) and plot the average risk perceptions against the decile rank in Figure A.3. Perceived risks decline as one's earnings increase. This is not exactly consistent with the uptick in income risks for the highest income group, as documented by Bloom et al. (2018) using tax records of income. The most likely explanation is that the small sample I used from SCE does not cover actual top earners. The average annual earning of the top income group is between $45,000 and $120,000 in our sample.

**Figure A.3:** Perceived Wage Risks by Earning Decile

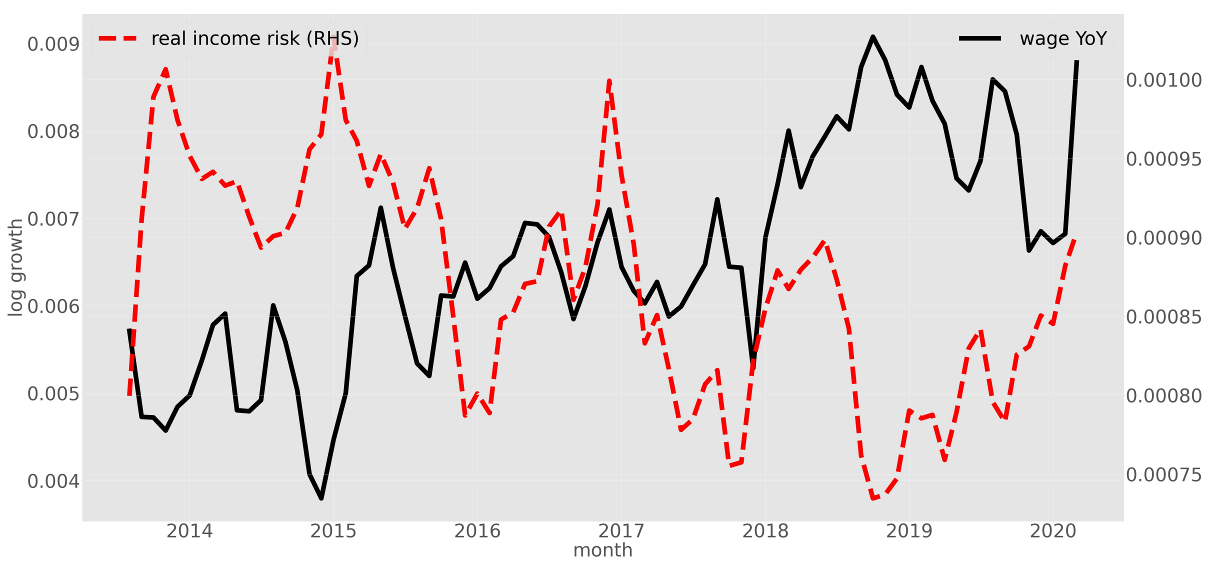



Note: this figure plots average perceived income risks by the decile of annual earning of the same individual.

### A.2.3 Counter-cyclicality of perceived risk

Some studies have documented that income risks are counter-cyclical based on cross-sectional income data. [49] It is worth inspecting if the subjective income risk profile has a similar pattern. Figure A.4 plots the average perceived income risks from SCE against the YoY growth of the average hourly wage across the United States, which shows a clear negative correlation. Table A.1 further confirms such a counter-cyclicality by reporting the regression coefficients of different measures of average risks on the wage rate of different lags. All coefficients are significantly negative.

**Figure A.4:** Recent Labor Market Conditions and Perceived Risks




Note: recent labor market outcome is measured by hourly wage growth (YoY). The 3-month moving average is plotted for both series.

The pattern can also be seen at the state level. Table A.2 reports the regression coefficients of the monthly average perceived risk within each state on the state labor market conditions, measured by either wage growth or the state-level unemployment rate, respectively. It shows that

[49]But they differ in exactly which moments of the income are counter-cyclical. For instance, Storesletten et al. (2004) found that variances of income shocks are counter-cyclical, while Guvenen et al. (2014) and Catherine (2019), in contrast, found it to be the left skewness.

**Table A.1:** Current Labor Market Conditions and Perceived Income Risks

| | mean:var | mean:iqr | mean:rvar | median:var | median:iqr | median:rvar |
|---|---|---|---|---|---|---|
| 0 | -0.28** | -0.42*** | -0.48*** | -0.16 | -0.16 | -0.53*** |
| 1 | -0.44*** | -0.54*** | -0.51*** | -0.02 | -0.02 | -0.53*** |
| 2 | -0.39*** | -0.44*** | -0.43*** | -0.05 | 0.0 | -0.45*** |
| 3 | -0.44*** | -0.47*** | -0.41*** | -0.09 | -0.06 | -0.5*** |
| 4 | -0.29** | -0.38*** | -0.32*** | -0.19 | -0.14 | -0.5*** |

*** $p<0.001$, ** $p<0.01$ and * $p<0.05$.

This table reports correlation coefficients between different perceived income moments(inc for nominal and rinc for real) at time $t$ and the quarterly growth rate in hourly earning at $t, t-1, ..., t-k$.

a tighter labor market (higher wage growth or a lower unemployment rate) is associated with lower perceived income risks. Note that our sample stops in June 2019 thus not covering the outbreak of the pandemic in early 2020. The counter-cyclicality will be very likely more salient if it includes the current period, which was marked by catastrophic labor market deterioration and increase market risks.

**Table A.2:** Average Perceived Risks and Local Labor Market Conditions

| | (1)<br>log perceived risk | (2)<br>log perceived risk | (3)<br>log perceived iqr | (4)<br>log perceived iqr |
|---|---|---|---|---|
| Wage Growth (Median) | -0.05*** | | -0.03*** | |
| | (0.01) | | (0.01) | |
| UE (Median) | | 0.04* | | 0.04*** |
| | | (0.02) | | (0.01) |
| Observations | 3589 | 3589 | 3596 | 3596 |
| R-squared | 0.021 | 0.019 | 0.025 | 0.027 |

*** $p<0.001$, ** $p<0.01$ and * $p<0.05$.

This table reports regression coefficient of the average perceived income risk of each state in different times on current labor market indicators, i.e. wage growth and unemployment rate. Monthly state wage series is from Local Area Unemployment Statistics (LAUS) of BLS. Quarterly state unemployment rate is from Quarterly Census of Employment and Wage (QCEW) of BLS.

The counter-cyclicality in subjective risk perceptions seen in the survey may suggest the standard assumption of state-independent symmetry in income shocks is questionable. But it may well be, alternatively, because people's subjective reaction to the positive and negative shocks are asymmetric even if the underlying process being symmetric.

### A.2.4 Experiences and perceived risk

**Table A.3:** Extrapolation from Recent Experience

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| income shock squared | 0.0225*** | 0.0222*** | 0.0217*** | 0.0207*** | 0.000773 | 0.00205*** | 0.000566 | 0.00183*** | 0.000614 | 0.00184*** |
| | (0.00562) | (0.00570) | (0.00562) | (0.00564) | (0.000743) | (0.000516) | (0.000744) | (0.000515) | (0.000745) | (0.000516) |
| recently unemployed | | | | 0.511* | 0.228*** | 0.0895*** | | | | |
| | | | | (0.260) | (0.0330) | (0.0200) | | | | |
| unemployed since m-8 | | | | | | | 0.161*** | 0.0783*** | | |
| | | | | | | | (0.0207) | (0.0121) | | |
| unemployed since y-1 | | | | | | | | | 0.138*** | 0.0701*** |
| | | | | | | | | | (0.0193) | (0.0113) |
| Observations | 3662 | 3662 | 3662 | 3662 | 3701 | 1871 | 3701 | 1871 | 3701 | 1871 |
| R-squared | 0.004 | 0.013 | 0.016 | 0.017 | 0.015 | 0.030 | 0.019 | 0.041 | 0.016 | 0.039 |

Standard errors are clustered by household. *** p<0.001, ** p<0.01 and * p<0.05.
This table reports regression of perceived risks and perceived unemployment risks on recent experiences of income volatility and the dummy indicating if the individual has recently experienced an unemployment.

Different generations also have different perceived income risks. Let us explore to what extent the cohort-specific risk perceptions are influenced by the income volatility experienced by that particular cohort. Different cohorts usually have experienced distinct macroeconomic and individual histories. On one hand, these non-identical experiences could lead to long-lasting differences in realized life-long outcomes. An example is that college graduates graduating during recessions have lower life-long income than others. (Kahn (2010), Oreopoulos et al. (2012), Schwandt and Von Wachter (2019)). On the other hand, experiences may have also shaped people's expectations directly, leading to behavioral heterogeneity across cohorts (Malmendier and Nagel (2015)). Benefiting from having direct access to the subjective income risk perceptions, I could directly examine the relationship between experiences and perceptions.

Individuals from each cohort are borned in the same year and obtained the same level of their respective highest education. The experienced volatility specific to a certain cohort $c$ at a given time $t$ can be approximated as the average squared residuals from an income regression based on the historical sample only available to the cohort's life time. This is approximately the unexpected income changes of each person in the sample. I use the labor income panel data from PSID to estimate the income shocks. [50] In particular, I first undertake a Mincer-style regression using major demographic variables as regressors, including age, age polynomials, education, gender and time-fixed effect. Then, for each cohort-time sample, the regression mean-squared error (RMSE) is used as the approximate to the cohort/time-specific income volatility.

There are two issues associated with such an approximation of experienced volatility. First, I, as an economist with $PSID$ data in my hand, am obviously equipped with a much larger sample than the sample size facing an individual that may have entered her experience. Since larger sample also results in a smaller RMSE, my approximation might be smaller than the real experienced volatility. Second, however, the counteracting effect comes from the superior information problem, i.e. the information set held by earners in the sample contains what is not available to econometricians. Therefore, not all known factors predictable by the individual are used as a regressor. This will bias upward the estimated experienced volatility. Despite these concerns, my method serves as a feasible approximation sufficient for my purpose here.

The right figure in Figure A.5 plots the (logged) average perceived risk from each cohort $c$ at year $t$ against the (logged) experienced volatility estimated from above. It shows a clear positive correlation between the two, which suggests that cohorts who have experienced higher income volatility also perceived future income to be riskier. The results are reconfirmed in Table A.4, for which I run a regression of logged perceived risks of each individual in SCE on the logged experienced volatility specific to her cohort while controlling individuals age, income, educations, etc. What is interesting is that the coefficient of *expvol* declines from 0.73 to 0.41 when controlling the age

[50] I obtain the labor income records of all household heads between 1970-2017. Farm workers, youth and olds and observations with empty entries of major demographic variables are dropped.

effect because that variations in experienced volatility are indeed partly from age differences. While controlling more individual factors, the effect of the experienced volatility becomes even stronger. This implies potential heterogeneity as to how experience was translated into perceived risks.

How does experienced income shock per se affect risk perceptions? We can also explore the question by approximating experienced income growth as the growth in unexplained residuals. As shown in the left figure of Figure A.5, it turns out that a better past labor market outcome experienced by the cohort is associated with lower risk perceptions. This indicates that it is not just the volatility, but also the change in level of the income, that is asymmetrically extrapolated into their perceptions of risks.

### A.2.5 Perceived Risks and Individual Characteristics

Table A.4 reports the regression results of individual PRs on individual variables with various specifications.

## A.3 Wage risk estimation using SIPP data

### A.3.1 Sample selection

To estimate the wage risks, or risks to the earning conditional on working for the same hours and staying in the same job, I restrict the universe of the SIPP sample according to this definition for the worker's primary job (JB1). The specific filtering criteria is listed as below, and it is approximately identical to that in Low et al. (2010) for computing the wage rate of the same job using 1993 panel of SIPP.

- Time: January 2013-December 2020

- Age: 20 - 60

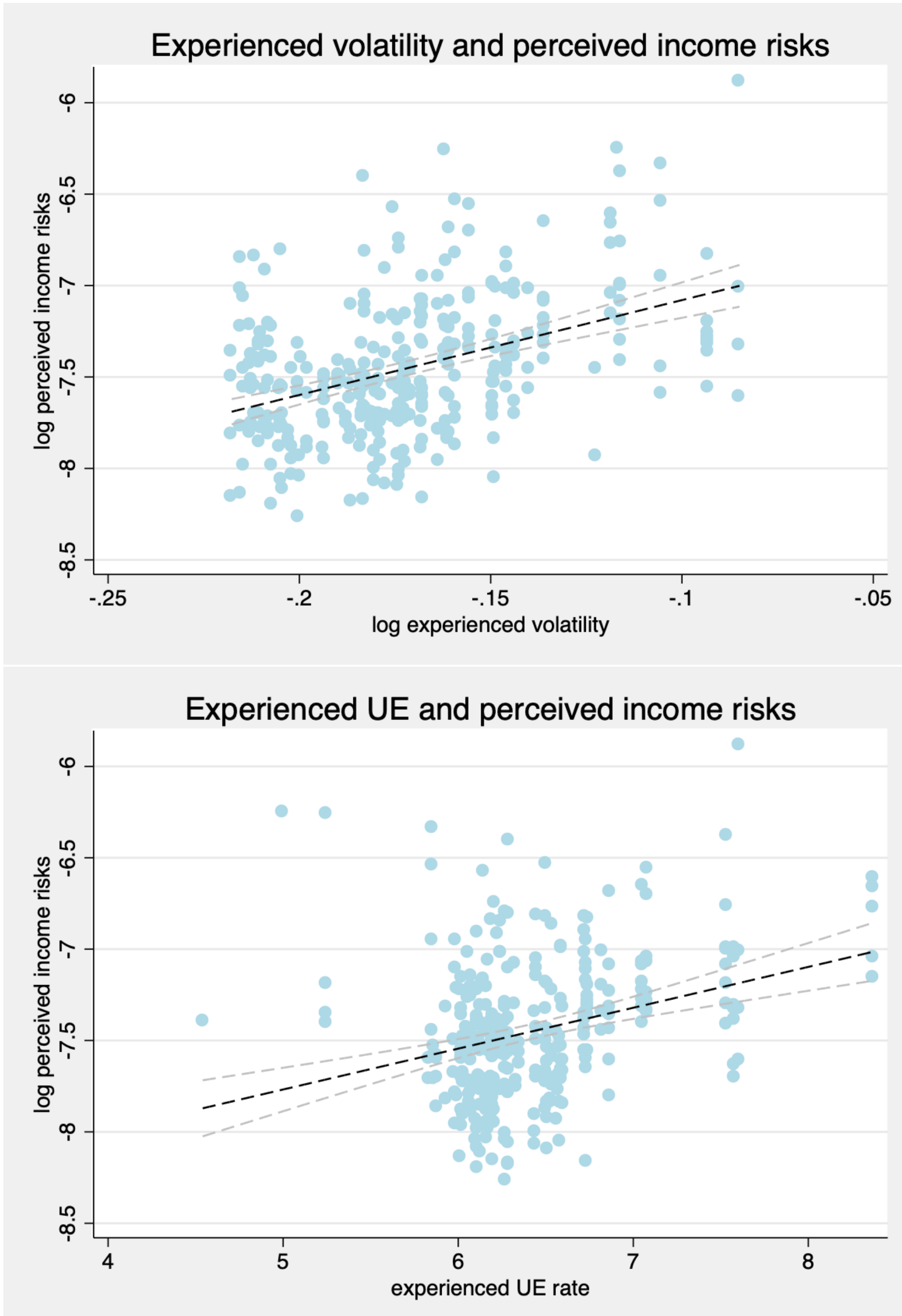
**Table A.4:** Covariants of Perceived Wage Risks

| | incvar I | incvar II | incvar III | incvar IIII | incvar IIIII | incvar IIIIII |
|---|---|---|---|---|---|---|
| IdExpVol | 4.58*** | 2.23*** | 2.69*** | 2.75*** | 2.95*** | 2.94*** |
| | (0.33) | (0.36) | (0.39) | (0.39) | (0.38) | (0.39) |
| AgExpVol | 0.04 | 0.28*** | 0.34*** | 0.32*** | 0.18*** | 0.20*** |
| | (0.04) | (0.04) | (0.05) | (0.05) | (0.05) | (0.05) |
| AgExpUE | 0.14*** | 0.08*** | 0.05** | 0.05* | 0.04* | 0.05** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| age | | -0.02*** | -0.02*** | -0.02*** | -0.02*** | -0.02*** |
| | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| gender=male | | | -0.36*** | -0.35*** | -0.32*** | -0.30*** |
| | | | (0.02) | (0.02) | (0.02) | (0.02) |
| nlit_gr=low nlit | | | 0.09*** | 0.09*** | 0.10*** | 0.09*** |
| | | | (0.02) | (0.02) | (0.02) | (0.02) |
| parttime=yes | | | | | -0.01 | -0.02 |
| | | | | | (0.02) | (0.02) |
| selfemp=yes | | | | | 1.25*** | -0.00*** |
| | | | | | (0.03) | (0.00) |
| UEprobAgg | | | | | | 0.02*** |
| | | | | | | (0.00) |
| UEprobInd | | | | | | 0.02*** |
| | | | | | | (0.00) |
| HHinc_gr=low income | | | | | 0.16*** | 0.16*** |
| | | | | | (0.02) | (0.02) |
| educ_gr=high school | | | | -0.10*** | -0.13*** | -0.09*** |
| | | | | (0.02) | (0.02) | (0.02) |
| educ_gr=hs dropout | | | | 0.08 | 0.11 | 0.29*** |
| | | | | (0.11) | (0.11) | (0.11) |
| N | 41422 | 41422 | 34833 | 34833 | 33480 | 29687 |
| R2 | 0.01 | 0.02 | 0.04 | 0.04 | 0.11 | 0.06 |

Standard errors are clustered by household. *** $p<0.001$, ** $p<0.01$ and * $p<0.05$.

This table reports results associated a regression of logged perceived income risks (incvar) on logged idiosyncratic(IdExpVol), aggregate experienced volatility(AgExpVol), experienced unemployment rate (AgExpUE), and a list of household specific variables such as age, income, education, gender, job type and other economic expectations.

**Figure A.5:** Experience and Perceived Income Risk




Note: the experienced income volatility is the cross-sectional variance of log change in income residuals estimated using a sub sample restricted to the lifetime of a particular group. For instance, the life experience of a 25-year old till 2015 spans from 1990-2015. The perceived income risk is the average across all individuals from the cohort in that year. Cohorts are time/year-of-birth specific and all cohort sized 30 or smaller are excluded.

- Work-arrangement: employed by someone else (excluding self-employment and other work-arrangement): EJB1_JBORSE ==1.

- Employer: staying with the same employer for a tenure longer than 4 months: the same EJB1_JOBID for 4 or more consecutive months.

- Wage: total monthly earning from the primary job divided by the average number of hours worked in the same job, wage = TJB1_MSUM/TJB1_MWKHRS.

- Outliers: drop observations with wage rate lower than 0.1 or greater than 2.5 times of the individual's average wage.

- No days off from work without pay: EJB1_AWOP1 = 2.

- Continued job spell since December of the last year: RJB1_CFLG=1.

- Drop imputed values: EINTTYPE==1 or 2.

- Drop government/agriculture jobs: drop if TJB1_IND>=9400.

Based on the selected sample, Table A.5 reports the size and approximated group-specific wage volatility as defined in Equation 4.

**Table A.5:** Summary statistics of SIPP sample

| | Obs | Volatility |
|---|---|---|
| Year | | |
| 2013 (17%) | 9,815 | 0.06 |
| 2014 (20%) | 12,672 | 0.11 |
| 2015 (15%) | 9,543 | 0.1 |
| 2016 (9%) | 6,128 | 0.11 |
| 2017 (13%) | 7,533 | 0.07 |
| 2018 (15%) | 9,378 | 0.13 |
| 2019 (8%) | 5,507 | 0.12 |
| Education | | |
| HS dropout (22%) | 13,846 | 0.09 |
| HS graduate (46%) | 28,385 | 0.1 |
| College/above (30%) | 18,345 | 0.12 |
| Gender | | |
| male (55%) | 33,842 | 0.1 |
| female (44%) | 26,734 | 0.11 |
| Full sample (100%) | 60,576 | 0.1 |

### A.3.2 SEAM Effect

One special feature of SIPP is that it collects monthly information by surveying each correspondent every four months before the 2013 wave and once a year afterward (since 2014 wave). This leads to the well-documented issue of SEAM effect (Ryscavage, 1993; Rips et al., 2003; Nekarda, 2008; Callegaro, 2008), which states that reported changes in survey answers are relatively small for adjacent months within a survey wave but much more abrupt between months across surveys. Such a difference could be either due to underreporting of changes within a reference period (due to reasons such as the recall bias) or overreporting of changes across reference periods.

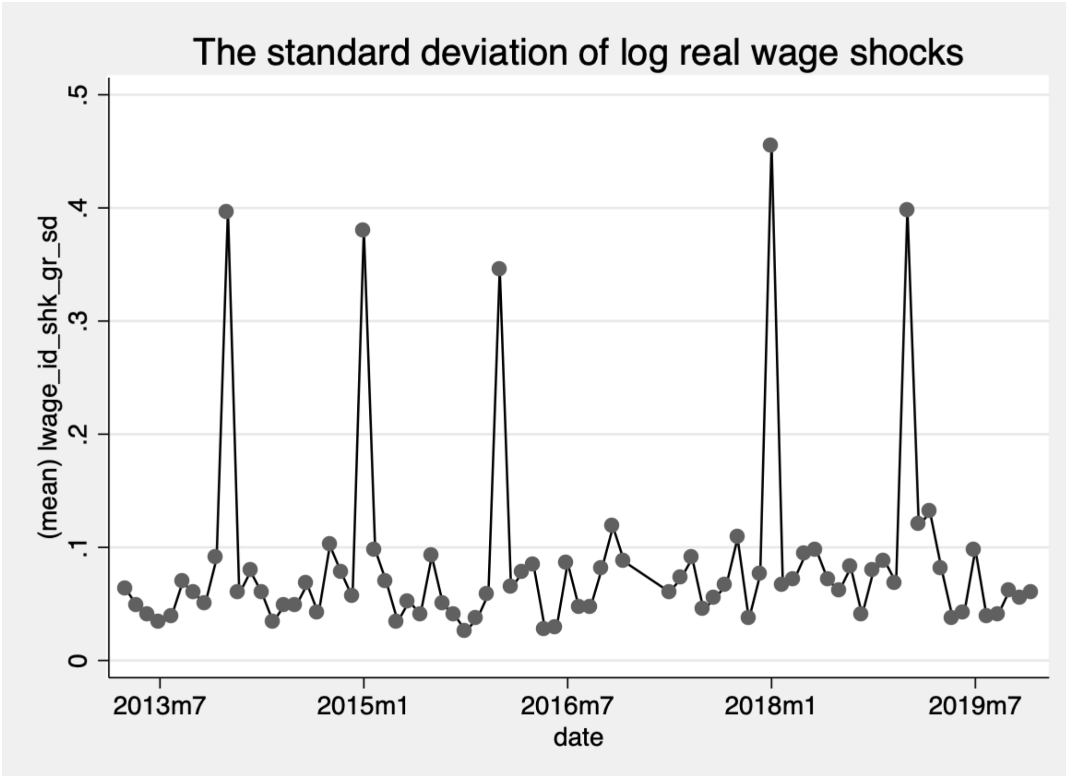
This effect is clearly seen from the time series plot of monthly wage volatility in Figure A.6, where there is always a spike in the size of volatility between December to January in the sample period.[51]

Because of this issue, for monthly risk estimation, I exclude the December-January observations, leading to non-identification of the risks of each January. By doing so, I basically assume that within-wave respondents do not underreport true changes to the wages, while the cross-wave answers overreport these changes. But the opposite assumption might be true, in that respondents underreport changes within the reference year when they retroactively answer survey questions, and the changes across reference periods are correctly reported.

One way to incorporate the cross-wage changes instead of dropping them by brutal force is to estimate risks at a lower frequency, i.e. quarterly and yearly, and construct the quarterly/yearly period such that it covers the cross-wave cutoff month December. Figure A.9 and A.10 in section A.4.3 plot the time-varying risks estimated for quarterly and annual frequency, respectively.

[51]Note that the only exception is January 2017, for which no monthly growth rate is not available due to reshuffling of the SIPP sample.

**Figure A.6:** Estimated monthly wage volatility




Note: this figure plots the monthly wage volatility as defined in Equation 4 for the entire selected sample, estimated from SIPP.

## A.4 Wage risk estimation under alternative assumptions

### A.4.1 Baseline estimation

Permanent and transitory risks are identified via the following moment restrictions.

$$\begin{aligned} &var(\Delta e_{i,t}) = var(\psi_t + \theta_t - \theta_{t-1}) = \sigma^2_{\psi,t} + \sigma^2_{\theta,t} + \sigma^2_{\theta,t-1} \\ &cov(\Delta e_{i,t}, \Delta e_{i,t+1}) = cov(\psi_t + \theta_t - \theta_{t-1}, \psi_{t+1} + \theta_{i,t+1} - \theta_{i,t}) = -\sigma^2_{\theta,t} \\ &cov(\Delta e_{i,t-1}, \Delta e_{i,t}) = cov(\psi_{t-1} + \theta_t - \theta_{t-1}, \psi_t + \theta_{i,t} - \theta_{i,t-1}) = -\sigma^2_{\theta,t-1} \end{aligned} \tag{24}$$

With four years of wage of individual $i$ from $t-2$ to $t$, hence three years of first difference $\Delta w$, the above three equations can exactly identify the permanent risk specific to time $t$, $\sigma_{\psi,t}$ and the time-specific transitory risk $\sigma_{\theta,t}$ and $\sigma_{\theta,t-1}$.

Three years of wage data is sufficient under a slightly looser restriction that the transitory risks stay constant over each 3-year horizon, between $t-1$ and $t+1$, call it $\bar{\sigma}_{\theta,t}$. In particular, we have the following identification. With wage growth in year 2014, 2015, 2016, and 2018, 2019, I can identify the year-specific permanent risks for 2014, 2015, 2016, 2018, and 2019, and the average transitory risks for 2014-2016 and 2017-2019, as shown in Figure A.9.

$$\begin{aligned} var(\Delta w_{i,t}) &= var(\psi_t + \theta_t - \theta_{t-1}) = \sigma^2_{\psi,t} + 2\bar{\sigma}^2_{\theta,t} \\ cov(\Delta w_{i,t}, \Delta w_{i,t+1}) &= cov(\Delta w_{i,t-1}, \Delta w_{i,t}) = -\bar{\sigma}^2_{\theta,t} \end{aligned} \tag{25}$$

**Figure A.7:** Monthly permanent and transitory income risks


Note: this figure plots the 3-month moving average of the estimated monthly permanent and transitory risks (variance) using the SIPP panel data on wage between 2013m1-2019m12.

### A.4.2 Evidence for the infrequent arrival of the wage shocks

The baseline income process specified as in Equation 2 has been commonly adopted for annual or at most quarterly income/wage data in the literature. But some recent work such as Druedahl et al. (2021) shows that income dynamics at a higher frequency, i.e. monthly, requires a modification to such a process to be more consistent with the data. In particular, the authors allow for infrequent arrivals of both transitory and permanent shocks. The assumption of infrequent shocks is primarily motivated by the observed pattern (as confirmed in Figure A.8 using nominal wage growth in SIPP)

**Table A.6:** Perceived risk, realized volatility and approximated risks of each group

| | PR(mean) | PR(median) | Volatility | RealizedRisk | PRisk | TRisk |
|---|---|---|---|---|---|---|
| gender | | | | | | |
| 1 (50%) | 0.03 | 0.022 | 0.105 | 0.115 | 0.109 | 0.0238 |
| 2 (49%) | 0.028 | 0.022 | 0.118 | 0.131 | 0.122 | 0.0322 |
| education group | | | | | | |
| HS dropout (0%) | 0.036 | 0.022 | 0.088 | 0.071 | 0.07 | 0.0063 |
| HS graduate (42%) | 0.03 | 0.022 | 0.096 | 0.098 | 0.094 | 0.0176 |
| College/above (56%) | 0.028 | 0.021 | 0.124 | 0.142 | 0.132 | 0.0357 |
| 5-year age | | | | | | |
| 20 (2%) | 0.037 | 0.031 | 0.094 | 0.069 | 0.068 | 0.0061 |
| 25 (12%) | 0.032 | 0.027 | 0.111 | 0.157 | 0.156 | 0.0083 |
| 30 (12%) | 0.03 | 0.023 | 0.116 | 0.112 | 0.098 | 0.0372 |
| 35 (13%) | 0.029 | 0.021 | 0.125 | 0.149 | 0.134 | 0.0524 |
| 40 (13%) | 0.028 | 0.02 | 0.1 | 0.119 | 0.111 | 0.0287 |
| 45 (14%) | 0.028 | 0.02 | 0.119 | 0.113 | 0.106 | 0.0224 |
| 50 (15%) | 0.027 | 0.019 | 0.095 | 0.1 | 0.096 | 0.0203 |
| 55 (15%) | 0.027 | 0.018 | 0.122 | 0.128 | 0.121 | 0.0283 |
| Full sample (100%) | 0.029 | 0.021 | 0.112 | 0.123 | 0.115 | 0.0279 |

This table reports estimated realized annual volatility, risks of different components, and the expected income volatility of different groups. All are expressed in standard deviation units.

that a sizable mass of individual monthly wage growth is concentrated around zero.

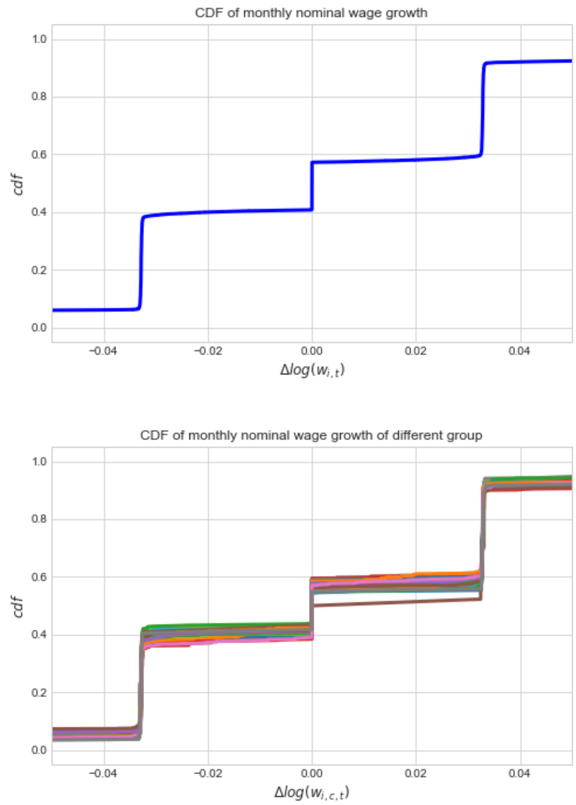
### A.4.3 Estimated risks at a lower frequency

Most of the income risk estimation in the literature is done at a lower frequency, such as yearly and quarterly. Figure A.9 plots the estimated time-varying permanent and transitory risks using annual growth of average wage of each year in the sample.[52] Due to reshuffling of the entire of SIPP sample in 2017, no annual wage growth rate can be calculated in 2017, hence, the permanent risks of 2017 and the transitory risks of its adjacent years are unable to be identified.

For the years with identified risks, the estimated risks at annual frequency seems to be much larger than that commonly seen in the literature, as summarized in Table A.7. In particular, the size of the permanent shock ranges from 27% to 41%, in contrast to the standard estimation of

[52] A similar size of estimates is obtained when YOY growth of monthly wage is used.

**Figure A.8:** CDF of monthly wage growth

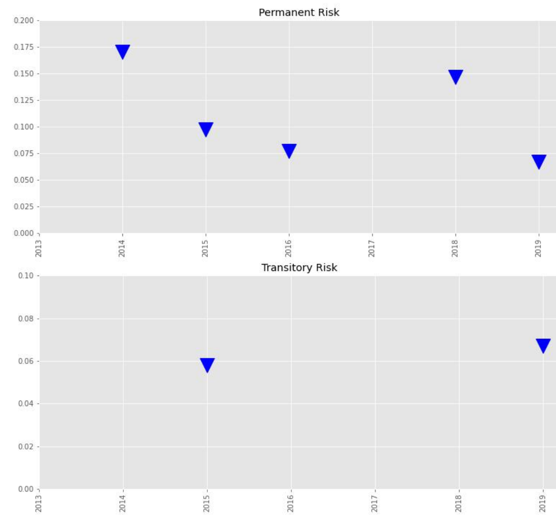



Note: this figure plots the cumulative distribution function of monthly wage growth from SIPP for the whole sample (left) and by gender-education-age-specific group (right).

10-15%. And the transitory risks are estimated to be around 25%, which also exceeds the standard estimates of 10% to 20%.

The similar issue can be seen from quarterly estimates using quarterly growth of average wage rates.(See Figure A.10) Reminiscent of the seasonal spike in the monthly volatility in January, there is a similar spike in the first quarter every year in the sample.

**Figure A.9:** Yearly permanent and transitory wage risks

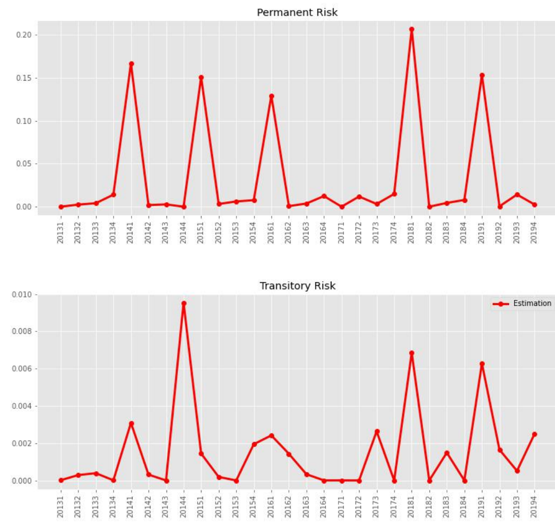



Note: this figure plots the estimated yearly permanent and transitory risks (variance) using the SIPP panel data on wage between 2013m1-2019m12.

## A.5 Results with the first moment (the expected and realized wage growth)

Although the main focus of this paper is on income/wage risks, specifically the second moment of wage growth, it is natural to ask if the expected wage growth revealed in SCE aligns with what is realized as seen in SIPP. It is not surprising that both expected and the realized average wage growth rate conditional on education and gender decline over the life-cycle, as shown in the downward fitted lines in Figure A.11. But In the sample of 2013-2019, expected wage growth seems to be persistently downward biased compared to its realization. This was not driven by the widely-documented fact of upward biased inflation expectation (See for instance, Wang (2022)), as even the same pattern shows up in the nominal wage growth.

**Figure A.10:** Quarterly permanent and transitory wage risks




Note: this figure plots the estimated quarterly permanent and transitory risks (variance) using the SIPP panel data on wage between 2013m1-2019m12.

## A.6 Homogenous and heterogeneous life-cycle wage profiles

Figure A.12 plots the deterministic wage profile used to calibrate the baseline model, which is estimated from SIPP for job-stayers. Figure A.13 plots the heterogeneous wage profiles used in the model experiment of $HPRURG$, which is calibrated based on the heterogeneous wage growth rates reported in SCE.

## A.7 Calibration heterogeneous income risks/growth rates using the survey

## A.8 Income risks in the existing literature

Table A.7 summarizes the most common estimates of income risks seen in the literature.

## A.9 Persistent/permanent effect of job loss in the existing literature

Table A.8 summarizes the estimated size of wage loss and change in income risks following job displacement and mass layoff, as reported in the literature.

## A.10 Estimating state-dependent PR using the survey

### A.10.1 The model

In this appendix section, I provide an alternative approach of estimating perceived risks using survey to that in 4.3. The central idea of this approach is to treat an individual's reported perceived risks as noisy signals of their true underlying yet unobservable risk belief that affects their decisions and assume that the survey answers are masked by measurement errors.

In particular, I assume the belief state is binary, i.e. low and high risks. Then the parameters to be estimated from the panel data of risk perceptions from $SCE$ are the state-dependent risk profile $\tilde{\Gamma}_l = \{\tilde{\sigma}^l_\psi, \tilde{\sigma}^l_\theta, \tilde{\mho}^l, \tilde{E}^l\}$, $\tilde{\Gamma}_h = \{\tilde{\sigma}^h_\psi, \tilde{\sigma}^h_\theta, \tilde{\mho}^h, \tilde{E}^h\}$ and $\Omega$, the transition matrix between the two states.

Denote the reported risk perception of the individual $i$ at time $t$ in the survey by $\tilde{\Gamma}^s_{i,t}$. It consists of the underlying risk perceptions relevant to individual decisions, or the model counterpart $\tilde{\Gamma}_{i,t}$, and an individual-specific, time-specific and an $i.i.d$ shock to the survey responses, respectively. The realization of $\tilde{\Gamma}_{i,t}$ depends on a hidden state $J_{i,t}$ which is non-observable to economists working with the survey data. It takes value of 1 if the individual $i$ is at a high-risk-perception state $\tilde{\Gamma}_{i,t} = \tilde{\Gamma}_h$

and zero if at low-risk-perceptions $\tilde{\Gamma}_{i,t} = \tilde{\Gamma}_l$. The $i.i.d$ shock $\epsilon_{i,t}$ is assumed to follow a mean-zero normal distribution with variance $\sigma^2_\epsilon$.

$$\underbrace{\tilde{\Gamma}^s_{i,t}}_{\text{reported PR}} = \underbrace{\tilde{\Gamma}_l + \mathbb{1}(\overbrace{J_{i,t}}^{\text{Hidden state}} = 1)(\tilde{\Gamma}_h - \tilde{\Gamma}_l)}_{\tilde{\Gamma}_{i,t}} + \xi_t + \eta_i + \epsilon_{i,t}$$

$$\text{Prob}(J_{i,t+1}|J_{i,t}) = \Omega$$

Notice that the individuals do not separately report their perceived risks for the permanent and transitory shocks, but instead the overall expected income volatility. Therefore, I make an auxiliary assumption that the agent adopts a constant ratio of decomposition between permanent and transitory risks, $\kappa = \frac{\tilde{\sigma}_{i,t,\psi}}{\tilde{\sigma}_{i,t,\theta}}$, the value of $\kappa$ is externally estimated from the realized income data.

In addition, since the surveyed risk perceptions is at the monthly frequency, I estimate the underlying risk parameters for monthly shocks. [53]

For each individual $i$, we observe at most 12 observations of their perceived income volatility of the earning growth next year $v\tilde{a}r_{i,t}$ from $t$ to $t+12$ and their job-separation and job-finding expectations, respectively. The panel structure allows the individual fixed effect $\eta_i$ and time-fixed effect $\xi_t$ to be easily identified.

Then the parameters can be estimated with a modified 2-regime Markov switching model a la Hamilton (1989) using the maximum-log-likelihood (MLE). (See the detailed implementation in Appendix A.10.2). Table A.9 reports the baseline estimates of the parameters associated with the 2-state Markov model of subjective perceptions. All parameters are converted from monthly into yearly counterparts to be consistent with the model frequency.

The estimates of subjective profile confirms the key finding we have detailed in the previous section. The estimated staying probabilities at low and high risk perceptions, $q$ and $p$, are around 0.9,

[53] $\tilde{\text{var}}_{i,t} = (12\tilde{\sigma}^2_{i,t,\psi} + 1/12\tilde{\sigma}^2_{i,t,\theta}) exp^{\xi_t} exp^{\eta_i} exp^{\epsilon_{i,t}} \rightarrow \log \tilde{\text{var}}_{i,t} = \log(12\tilde{\sigma}^2_{i,t,\psi} + 1/12\tilde{\sigma}^2_{i,t,\theta}) + \xi_t + \eta_i + \epsilon_{i,t} \rightarrow \log(\tilde{\text{var}}_{i,t}) = \log[(12 + \frac{1}{12\kappa^2})\tilde{\sigma}^2_{i,t,\psi}] + \xi_t + \eta_i + \epsilon_{i,t}$.

indicating a high degree of persistence in individual risk perceptions. Given these estimated transition probabilities, earning risk perceptions are on average lower than the objective level assumed in the literature.

### A.10.2 Details of the estimation

For each individual $i$, we observe at most 12 observations of their perceived income volatility over the earning growth next year $v\tilde{a}r_{i,t}$ from $t = 1$ to $= 12$. We assume the following relation between observed survey reported volatility and underlying perceived monthly permanent/transitory risks by the individual $i$ at time $t$.

$$\log \tilde{\text{var}}_{i,t} = \log(12\tilde{\sigma}^2_{i,t,\psi} + 1/12\tilde{\sigma}^2_{i,t,\theta}) + \xi_t + \eta_i + \epsilon_{i,t}$$

$\eta_i$ and $\xi_t$ are individual and time fixed effect, respectively. The i.i.d shock $\epsilon_{i,t}$ represents any factor that is not available to economists working with the survey, but affects $i$'s survey answers at the time $t$. We assume it is normally distributed.

Notice that $\tilde{\text{var}}_{i,t}$ alone is not enough to separately identify the perceived permanent and transitory risks. To proceed, I make the following auxiliary assumption: the agent adopts a constant ratio of decomposition between permanent and transitory risks, $\kappa = \frac{\tilde{\sigma}_{i,t,\psi}}{\tilde{\sigma}_{i,t,\theta}}$, the value of $\kappa$ is externally estimated from the realized income data.

With the additional assumption, we can rewrite the equation above, utilizing the fact that risks for one year are the cumulative sum of monthly ones for permanent shocks and the average of monthly ones for transitory shocks.

$$\log(\tilde{\text{var}}_{i,t}) = \log[(12 + \frac{1}{12\kappa^2})\tilde{\sigma}^2_{i,t,\psi}] + \xi_t + \eta_i + \epsilon_{i,t}$$

We *jointly* estimate a Markov-switching model on perceived volatility $\log(\tilde{\text{var}}_{i,t})$, perceived probability on unemployment status $\tilde{\mho}_{i,t}$, and perceived probability on employment status $\tilde{E}_{i,t}$. The vector model to be estimated can be represented as below.

$$\hat{\tilde{\Gamma}}^s_{i,t} = \tilde{\Gamma}^l + \mathbb{1}(J_{i,t} = 1)(\tilde{\Gamma}^h - \tilde{\Gamma}^l) + \tau_{i,t}$$

where $\hat{\tilde{\Gamma}}^s_{i,t} = [\log(\hat{\tilde{\text{var}}}_{i,t}), \hat{\tilde{\mho}}_{i,t}, \hat{\tilde{E}}_{i,t}]'$ is a vector of sized three, consisting of properly transformed reported risk perceptions from the survey, excluding the time and individual fixed effects in a first step regression. $J_{i,t} = 1$ for high risk state and $= 0$ if at the low risk state. $\tau_{i,t}$ is a vector of three i.i.d. normally distributed shocks.

The estimation of 2-regime Markov switching models produces estimates of $\tilde{\Gamma}_l$, $\tilde{\Gamma}_h$, the staying probability $q$, and $p$, and the variance of $\tau_{i,t}$. Then the following relationship can be used to recover perceived permanent and transitory risks respectively.

$$\tilde{\Gamma}^l = [\log[(12 + \frac{1}{12\kappa^2})\tilde{\sigma}^{l2}_{\psi}], \tilde{\mho}_l, \tilde{E}_l]'$$

$$\tilde{\Gamma}^h = [\log[(12 + \frac{1}{12\kappa^2})\tilde{\sigma}^{h2}_{\psi}], \tilde{\mho}_h, \tilde{E}_h]'$$

**Estimation sample** I restrict the sample to SCE respondents who were surveyed for at least 6 consecutive months with non-empty reported perceived earning volatility, separation and job-finding expectations. This left with me 6457 individuals.

Table A.9 reports the estimated parameters.

## A.11 Model extension: state-dependent risk perceptions

In the benchmark model, I maintain the FIRE assumption that the agents perfectly know the underlying parameters of income risks $\Gamma = \{\sigma^2_{\psi}, \sigma^2_{\theta}, \mho, E\}$ as assumed by the modelers and behave optimally accordingly.

But here, I relax the FIRE assumption by separately treating the "true" underlying risk parameters $\Gamma$ and the risk perceptions held by the agents. The latter is denoted as $\tilde{\Gamma}_i$. This extension is meant to capture the four empirical patterns documented in the previous sections.

1. Underestimation of the earning risks (compared to what is assumed to be the truth in the model)

2. Heterogeneity in risk perceptions

3. Extrapolation of recent experiences

4. State-dependence of risk perceptions

The possible approaches of capturing these perceptual patterns are by no means unique. I adopt one simple framework that does not require explicitly specified mechanisms of perception formation but sufficient to reflect these the patterns revealed from the survey data.

Assume that each agent $i$ in the economy cannot directly observe the underlying risk parameters $\Gamma$, but instead make his/her best choices based on a subjective risk perceptions $\tilde{\Gamma}_{i,\tau}$, which swing between two states: $\tilde{\Gamma}_l$ (low risk) and $\tilde{\Gamma}_h$ (high risk). The transition between the two states is governed by a Markov process with a transition matrix $\Omega$. In the calibration of the model in latter sections, these subjective parameters can be estimated from survey data relied upon auxiliary assumptions.

Such an assumption automatically allows for heterogeneity in risk perceptions across different agents at any point of the time. All individuals are distributed between low and high risk-perception states.

The transition probability between low-risk and high-risk perception states can be also configured so that the average risk perception is lower than the true level of the risk. If we let the transition matrix $\Omega$ to be dependent on individual unemployment status $\nu_{i,\tau}$, or macroeconomic conditions, we can also easily accommodate the possibility of experience extrapolation and state-dependence feature of risk perceptions.

Under the assumption of subjective perception, the subjective state of the risk perceptions $\tilde{\Gamma}$ becomes an additional state variable entering the Bellman equation of the consumer's problem, restated in below.

$$\tilde{V}_\tau(\tilde{\Gamma}_\tau, \nu_\tau, m_\tau, p_\tau) = \max_{\{c_\tau\}} \quad u(c_\tau) + (1-D)\beta\mathbb{E}_\tau\left[\tilde{V}_{\tau+1}(\tilde{\Gamma}_{\tau+1}, \nu_\tau, m_{\tau+1}, p_{\tau+1})\right] \tag{26}$$

Notice here that I assume that the agents recognize the transition between two subjective perception states and take it into account when making the best choices. This assumption guarantees time-consistency and provides additional discipline to the model assumption.

The consumer's solution to the problem above is the age-specific consumption policy $\tilde{c}^*_\tau(\tilde{\Gamma}_\tau, u_\tau, m_\tau, p_\tau)$ that is also a function of subject risk perception state $\tilde{\Gamma}$.

The distinction between objective and subject risk perception marks the single most important deviation of this paper from existing incomplete-market macro papers. [54] There is a long tradition of explicitly incorporating various kinds of heterogeneity in addition to uninsured idiosyncratic income shocks in these kinds of models to achieve better match with observed cross-sectional wealth inequality. One of the most notable assumptions used in the literature is the heterogeneity in time preferences (Krusell and Smith (1998), Carroll et al. (2017), Krueger et al. (2016)). My modeling approach shares the spirit with and are not mutually exclusive to these existing assumptions on preferential heterogeneity. But, to some extent, perceptual heterogeneity is more preferable as such patterns are directly observed from the survey data, as I show in the previous part of the paper.

A more fundamental justification for such a deviation from the full information rational ex-

[54] For instance, Bewley (1976), Huggett (1993), Aiyagari (1994), Krusell and Smith (1998), Krueger et al. (2016), Carroll et al. (2017).

pectation assumption is that risk parameters $\Gamma$ are barely observable objects to agents. This is so no matter if they are exogenously assumed by economists or endogenously determined in the equilibrium of the model. [55] Therefore, the conventional argument in favor of rational expectation assumption, namely equilibrium outcome drives the agents' perceptions to converge to the "truth", does not apply here.

Incorporating subjective risk perceptions also alters aggregate dynamics of the distributions as described in Equation 22, as restated below.

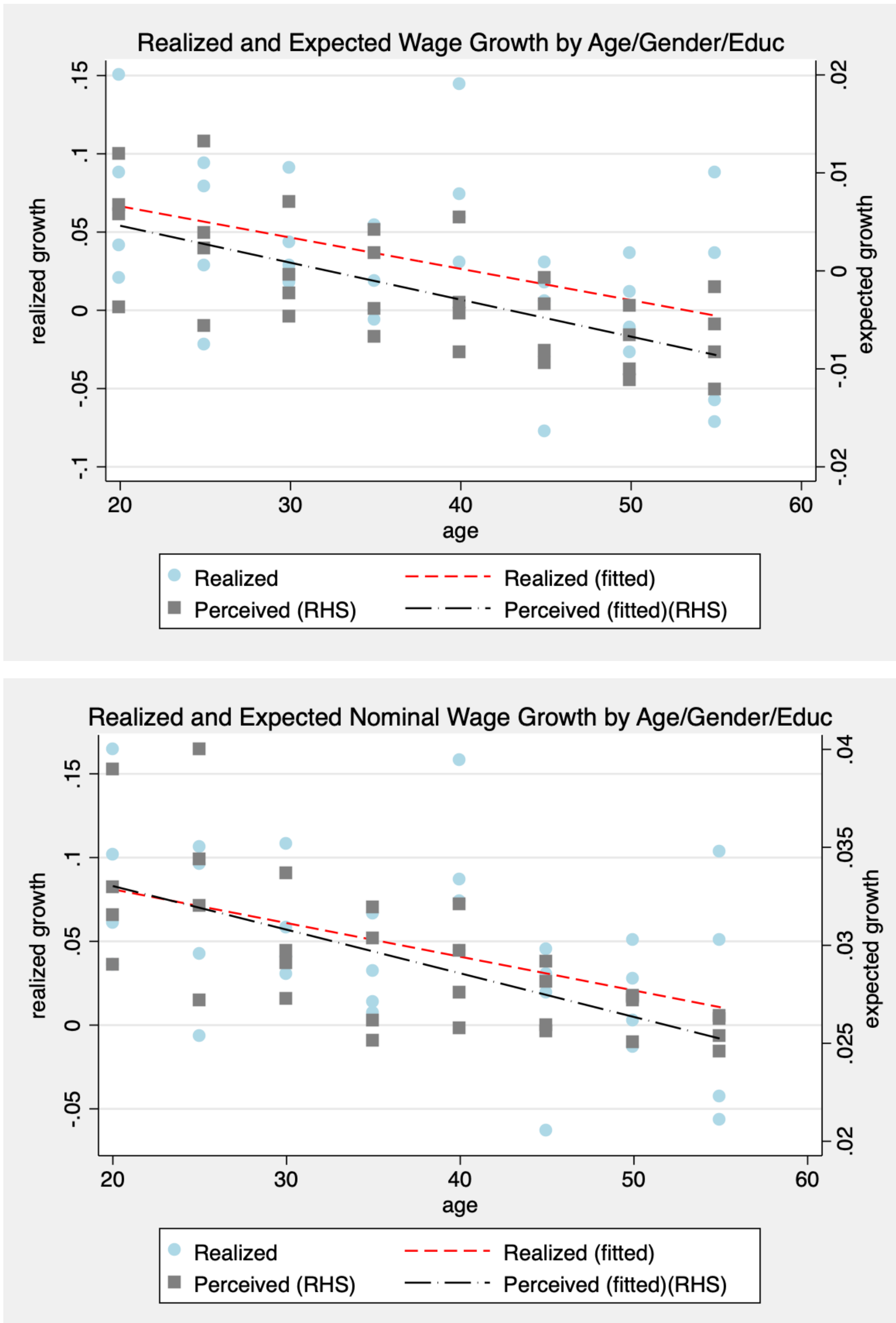
$$\tilde{\psi}_{\tau-1}(\tilde{B}) = \int_{\tilde{x}\in\tilde{X}} \tilde{P}(\tilde{x}, \tau-1, \tilde{B}) \mathrm{d}\tilde{\psi}_{\tau-1} \quad \text{for all} \quad \tilde{B} \in \tilde{B}(X) \tag{27}$$

The state variable $\tilde{x}$ includes subjective state $\tilde{\Gamma}$ in addition to those contained in $x$. The transition probabilities $\tilde{P}$ now depend on the optimal consumption policies $c^*(\tilde{x})$ as a function of belief state $\tilde{\Gamma}$, as well as the exogenous transition probabilities of the true stochastic income process $\Gamma$.

Then the new StE under subjective risk perceptions can be defined accordingly.

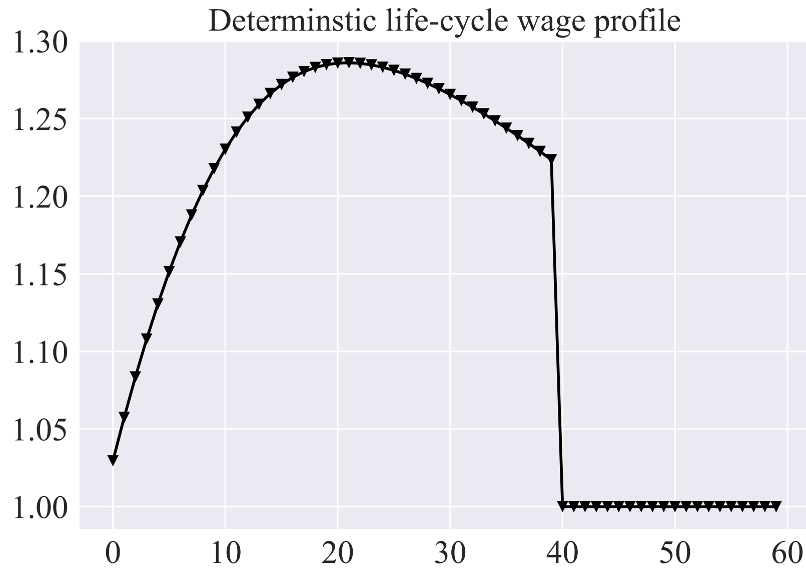
[55] So far, the majority workhorse incomplete market macro literature has not incorporated any endogenous mechanisms that determine the level of income risks. The emerging literature that incorporates labor market search/match frictions in these models have relied upon simplifying assumptions to get tractability. See, for instance, McKay (2017); Acharya and Dogra (2020); Ravn and Sterk (2021), with the only exception being Ravn and Sterk (2017).

**Figure A.11:** Realized and Perceived Income Growth over the Life Cycle



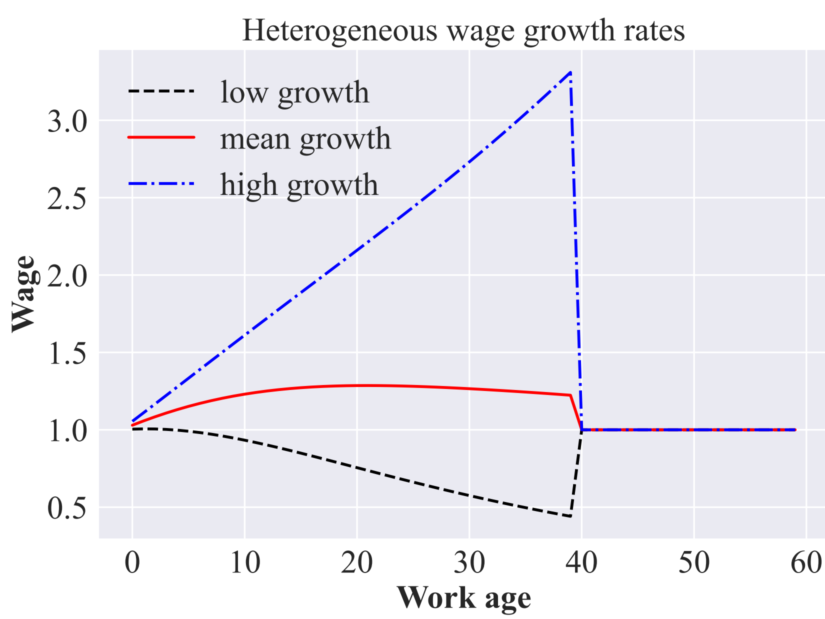

Note: this figure plots the average real (upper panel) and nominal (bottom panel) realized and perceived wage growth of different age groups, conditional on the gender and education of the individual. The realized wage growth is approximated by the average log changes in real wage of each age/education/gender group based on SIPP.

**Figure A.12:** Estimated deterministic wage profile over the life-cycle



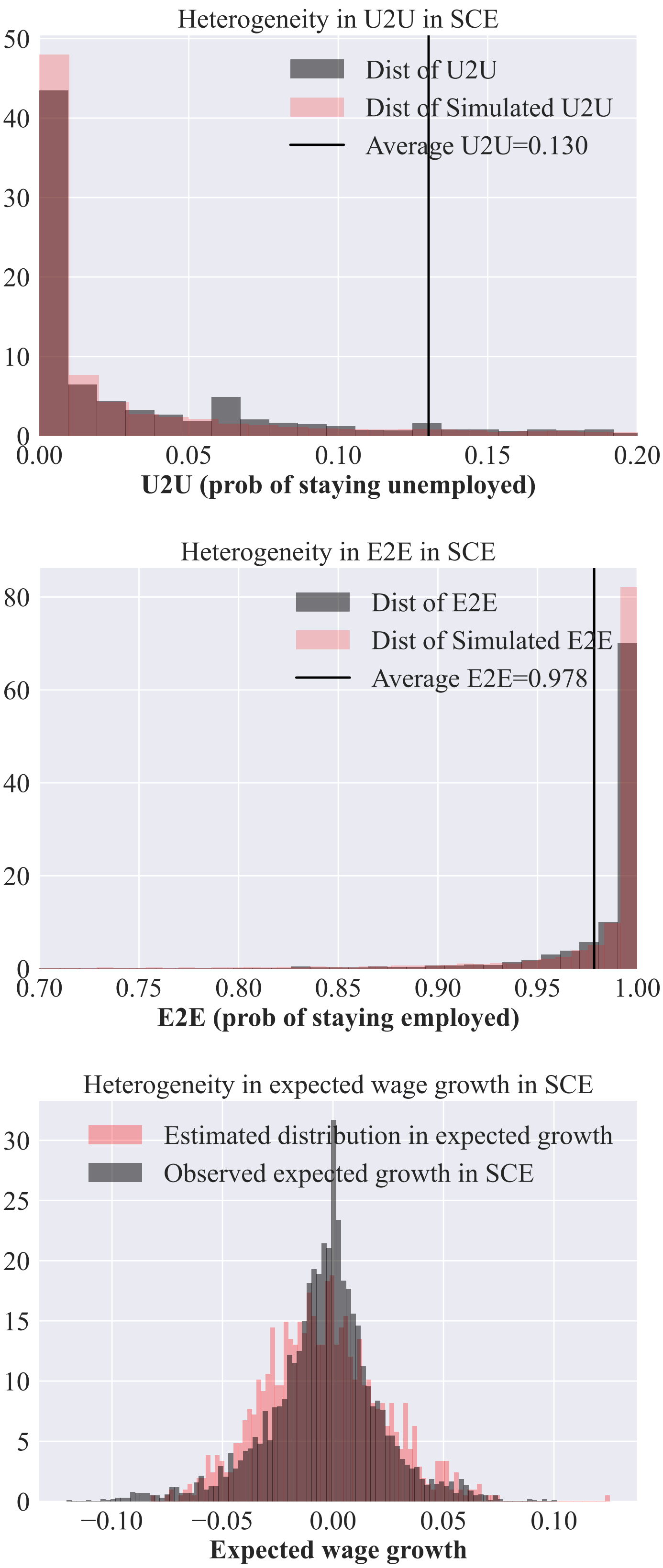

Note: this figure plots the estimated average age profile of real earnings using SIPP between 2013m3-2019m12. It is based on a regression of fourth-order age polynomials controlling for time, education, occupations, gender, etc.

**Figure A.13:** Heterogeneous wage profiles over the life-cycle




Note: this figure plots the heterogeneous deterministic wage profiles implied by the heterogeneous wage growth rates. This is used to calibrate the $HPRURG$ model.

**Figure A.14:** Calibration of heterogeneous UE risks and wage growth rates from the SCE




This figure illustrates the calibration of unemployment risks, and wage growths using SCE.

**Table A.7:** The size and nature of idiosyncratic income risks in the literature

| | $\sigma_\psi$ | $\sigma_\theta$ | $\mho$ | $E$ | Earning Process | Unemployment | Source |
|---|---|---|---|---|---|---|---|
| Huggett (1996) | [0.21,+] | N/A | N/A | N/A | AR(1) | No | Page 480 |
| Krusell and Smith (1998) | N/A | N/A | [0.04,0.1] | [0.9,0.96] | N/A | Persistent | Page 876 |
| Cagetti (2003) | [0.264, 0.348] | N/A | N/A | N/A | Random +MA innovations | No | Page 344 |
| Gourinchas and Parker (2002) | [0.108,0.166] | [0.18, 0.256] | 0.003 | 0.997 | Permanent +transitory | Transitory | Table 1 |
| Meghir and Pistaferri (2004) | 0.173 | [0.09, 0.21] | N/A | N/A | Permanent +MA | No | Table 3 |
| Storesletten et al. (2004) | [0.094; +] | 0.255 | N/A | N/A | Persistent + transitory | No | Table 2 |
| Blundell et al. (2008) | [0.1,+] | [0.169,+] | N/A | N/A | Permanent + MA | No | Table 6 |
| Low et al. (2010) | [0.095,0.106] | 0.08 | 0.028 | N/A | Permanent+transitory with job mobility | Persistent | Table 1 |
| Kaplan and Violante (2014) | 0.11 | N/A | N/A | N/A | Persistent | No | Page 1220 |
| Krueger et al. (2016) | [0.196,+] | 0.23 | [0.046,0.095] | [0.894,0.95] | Persistent +transitory | Persistent | Page 26 |
| Carroll et al. (2017) | 0.10 | 0.10 | 0.07 | 0.93 | Permanent+transitory | Transitory | Table 2 |
| Bayer et al. (2019) | 0.148 | 0.693 | N/A | N/A | Persistent time+MA | No | Table 1 |
| My Estimates based on SIPP | 0.10 | 0.016 | N/A | N/A | Permanent +transitory | No | Table A.1 |

This table summarizes the conservative (lower bound) estimates/parameterization on idiosyncratic income risks at the annual frequency seen in the literature.

**Table A.8:** Summary of the literature on persistent/permanent effect from job displacement

| | Loss (nb of years after displacement) | Income risks | Period | Variables | Data/Sample |
|---|---|---|---|---|---|
| Ruhm (1991) | 10%-13%(4) | NA | 1969-1982 | Earning | PSID |
| Jacobson et al. (1993) | 25%(6) | NA | 1974-1986 | Earning | Administrative records of Pennsylvanian. |
| von Wachter et al. (2009) | 21%-27%(20) | NA | 1978-2004 | Earning | Social security records, and firm-level employment data. |
| Couch and Placzek (2010) | 13%-15% (6) | NA | 1993-2004 | Earning | Administrative data of Connecticut |
| Low et al. (2010) | 6%-9%(1) | 20% | Model | Wage rate | Model |
| Davis and Von Wachter (2011) | 10%-20%(20) | NA | 1980-2005 | Earning | Social security records |
| Farber (2017) | 6.2% (0) | Lower E2E rate | 1984-2016 | Wage rate | Displaced Workers Surveys (DWS) |
| Lachowska et al. (2020) | 16%(5) | NA | 2002-2014 | Wage rate | Employment Security Department of Washington state. |
| Pytka and Gulyas (2021) | 6% (11) (median) | NA | 1984-2017 | Earning | Austrian social security records |

This table summarizes the empirical estimates on earning/wage loss from job-displacement. For Farber (2017), the loss is computed as the combined effect for those re-employed at a full-time and a part-time job. For Pytka and Gulyas (2021), I converted the accumulated loss into an annual percentage loss.

**Table A.9:** Estimated subjective risk perceptions

| | baseline |
|---|---|
| $std(\tilde{\sigma})$ | 1.203 |
| $q$ | 0.565 |
| $p$ | 0.565 |
| $\tilde{\sigma}^l_\psi$ | 0.897 |
| $\tilde{\sigma}^l_\theta$ | 0.021 |
| $\tilde{\sigma}^h_\psi$ | 1.140 |
| $\tilde{\sigma}^h_\theta$ | 0.027 |

This table reports estimates of the parameters for the 2-state Markov switching model of subjective risk perceptions. Risks are at the annual frequency.