Perceived versus Calibrated Income Risks in Heterogeneous-agent Consumption Models

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Abstract

Models of microeconomic consumption (including those used in HA-macro models) typically calibrate the size of income risk to match panel data on household income dynamics. But, for several reasons, what is measured as risk from such data may not correspond to the risk perceived by the agent. This paper instead uses data from the New York Fed's *Survey of Consumer Expectations* to directly calibrate perceived income risks. One of several examples of the implications of heterogeneity in perceived income risks is increased wealth inequality stemming from differential precautionary saving motives. I also explore the implications of the fact that the perceived risk is lower than the calibrated level either due to unobserved heterogeneity by researchers or over-confidence by the agents.

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

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1. Introduction

Income risks matter for both individual behavior and macroeconomic outcomes. Given 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. It is widely accepted on the basis of empirical research indicating that idiosyncratic income risks are at most partially insured (Blundell, Pistaferri, and Preston (2008)), and such market incompleteness leads to ex-post wealth inequality[1] and different degrees of marginal propensity to consume (MPC) (Krueger, Mitman, and Perri (2016); Carroll et al. (2017)). This also changes the mechanisms by which macroeconomic policies can affect economic outcomes.[2] Furthermore, aggregate movements in the degree of idiosyncratic income risks can drive time-varying precautionary saving motives–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 in this literature 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 who make decisions in the model.[4]

But this estimation practice has limitations. The method used by economists to calibrate the size and persistence of income risks as perceived by the agents is subject to problems such as those caused by unobserved heterogeneity or model mis-specification. The intuition behind this is simple: certain information, either the intrinsic heterogeneity of each individual or advance information about future income or risks that enter an agent's information set from time to time, is not directly observable by economists. If risks calibrated by economists based on flawed estimations differ from those perceived by agents, the model's implications will fail to match behavior even if the model is right (except for the miscalibration).

[1] Aiyagari (1994); Huggett (1996); Carroll and Samwick (1997); Krusell and Smith (1998).

[2] Krueger, Mitman, and Perri (2016), Kaplan, Moll, and Violante (2018), Auclert (2019).

[3] Challe and Ragot (2016); McKay (2017); Heathcote and Perri (2018); Kaplan and Violante (2018); Den Haan, Rendahl, and Riegler (2018); Bayer et al. (2019); Acharya and Dogra (2020); Ravn and Sterk (2021); Harmenberg and Öberg (2021).

[4] Some recent examples include Krueger, Mitman, and Perri (2016), Bayer et al. (2019), Kaplan, Moll, and Violante (2018).

This paper addresses this issue by utilizing the recently available density forecasts of labor income surveyed by the New York Fed's *Survey of Consumer Expectation* (SCE). Compared to the previous work that has studied partial insurance with expectational surveys,[5] this paper's most important innovation is its use of the SCE's 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, and they also report perceived job-finding and separation probabilities and answers to a set of expectation 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. Then, the second moment, 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 a direct measure of the perception of risk that presumably guides individual decisions.

With the individual-specific reported perceived risk (PR) in hand, I first confirm that the differences in mean risk across groups (age; gender; education; etc) measured by the conventional method do capture some between-group differences in the mean self-reported perceptions (e.g., low-income young females are measured as, and perceive themselves as, facing higher risk than middle-aged middle-income males). However, patterns do not often align between the two, i.e. perceived risks, unlike calibrated risks, decrease with education. More importantly, within every such group, there is also a great deal of heterogeneity in PR that is not captured by the conventional approach. The R^2 of regression of PR on the conventional explanatory variables is only about 0.1, indicating that 90 percent of the heterogeneity in perceived risk is not captured by the traditional method.

In addition, the paper also finds that the perceived income risk, on average, is *lower* than the indirectly calibrated size of risks even within groups. Specifically, the perceived annual real wage risk is around 3%-4% in terms of standard deviations, while the estimation following the conventional approach (consistent with the finding of Low, Meghir, and Pistaferri (2010)) is at least 10%. I confirm that this finding is robust to alternative specifications of the wage process, different frequencies of shocks, and the most conservative lower bound of the externally estimates of risks based on various income measures in the existing literature (Table A.3). This finding is corroborated by a closely related contemporaneous study Caplin et al. (2023) which also shows that survey-reported earning risks are lower than their indirectly estimated counterparts

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

using Danish administrative records.

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, Mitman, and Perri (2016) and Carroll et al. (2017). Contrasting with conventional practice, I show that calibrating risks using surveyed PRs helps reduce two well-documented discrepancies between standard model prediction and data regarding liquid wealth holdings of U.S. households: a higher concentration of households with little liquid wealth, the so-called"hands-to-mouth" consumers (H2M), and a higher degree of wealth inequality in the data than in the model.

Three forces together drive the model closer to the data. First, heterogeneity in perceived income risks increases inequality in precautionary wealth. Second, a lower size of the perceived risk than in the baseline model implies less precautionary saving motive, hence a lower level of wealth accumulation by all agents in the economy. Third, and less obvious, a lower degree of perceived risks implies a higher degree of predictable heterogeneity in wage growth rates, which translate to the heterogeneous saving behaviors.[6]

I also quantify the relative importance of perceived wage risks and unemployment risks in the improvement of the model fit: both components of income contribute to a higher wealth inequality, i.e. one-third and two-thirds, respectively of a total increase of wealth Gini by 13 percentage points. Meanwhile, the heterogeneity in unemployment risks is the key to accounting for a larger share of H2M closer to the data, i.e. an increase of 13 percentage points out of 17, in the share of H2M is attributed to realistically calibrating heterogeneous unemployment risks.

The benchmark model maintains the full-information-rational-expectation (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 this assumption. [7] In particular, the extension allows the perceived risks (subjective risks) to be different from the underlying income process (objective risks). This extension achieves two

[6] This echoes a number of studies that emphasize the role of heterogeneous income processes, in addition to risks, in accounting for income inequality: Guvenen (2007),Primiceri and Van Rens (2009).

[7] There is mounting evidence in macroeconomics that people form expectations in ways deviating from FIRE. See, for example, Mankiw, Reis, and Wolfers (2003), Reis (2006), Coibion and Gorodnichenko (2012), Wang (2022). However, most of such evidence is based on macroeconomic expectations, such as that of inflation.

purposes within a single model. First, it serves as a robustness check with an alternative model assumption deviating from FIRE. Although our benchmark assumes that agents' lower perceived risks than indirectly calibrated are due to the existence of unobserved heterogeneity, it is also possible that agents simply under-perceive the true degree of risks they face due to overconfidence. Second, the subjective model is an experimental model that breaks down the model implications into two channels: one via ex-ante saving behavior resulting from risk perceptions, or the "choice" channel, and the other via ex-post realized income inequality, the "outcome" channel.

The key finding from this extension is that "choice" channel is the key: letting consumption/saving decisions be driven by survey-reported risks alone, even if the objective risks remain the same as the conventional calibration, is sufficient to yield a closer match of the model with the empirically measured wealth inequality and the fraction of low-liquid-holding consumers. This reinforces a message that is echoed by many other studies based on expectation surveys: directly reported perceptions, albeit possibly subjective, still explain better the behaviors of heterogeneous agents and generate more realistic downstream macroeconomic implications than the indirectly calibrated expectations which often rely on strong assumptions.

1.1. Related literature

The closest to this paper in terms of the research question and findings is one contemporaneous study by Caplin et al. (2023). One key difference in research methodology between the two is how we compare subjective risks with their conventional counterparts. Caplin et al. (2023) first stimulates unconditional distributions of earnings based on surveyed belief and compares it with the cross-sectional Danish administrative records. In contrast, this paper estimates the conditional risks using a panel data structure following the common practice in income risks/HA-macro literature and compares it with conditional perceptions reported in the survey. Despite such differences in methodology and dataset, both studies find the perceived earning risks to be lower than those indirectly inferred from their conventional counterparts, which is primarily attributed to unobserved heterogeneity. Furthermore, the two studies explore the macroeconomic implications of subjective risks in two different contexts: this study works with a standard life-cycle incomplete market macro model a la Huggett (1993); Carroll and Samwick (1997); Krueger, Mitman, and Perri (2016); Carroll et al. (2017), with a primary focus on liquid wealth accumulation, while theirs works with a search and matching model.

Besides, this paper is related to and contributes to several themes in the literature. First, it closely builds on the literature estimating both cross-sectional and time trends of labor income risks and the degree of consumption insurance. Early work by MaCurdy (1982), Abowd and Card (1989), Gottschalk et al. (1994) and Carroll and Samwick (1997) initiated what is now the common practice in the literature of estimating income risks by decomposing it into components of varying persistence on the basis of panel data. Subsequent work has explored 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, Pistaferri, and Preston (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.[8] Moreover, recent evidence that relied upon detailed administrative records and larger data samples highlighted the asymmetry and cyclical behaviors of idiosyncratic earning/income risks (Storesletten, Telmer, and Yaron 2004; Guvenen, Ozkan, and Song 2014; Arellano, Blundell, and Bonhomme 2017; Guvenen et al. 2019; Bayer et al. 2019; Guvenen et al. 2021). Additionally, a separate literature has focused on job-separation and unemployment risks (Stephens Jr 2004; Low, Meghir, and Pistaferri 2010; Davis and Von Wachter 2011; Jäger et al. 2022). Table A.3 in the Appendix summarizes the income process and estimated risks in selected papers from this literature. Compared to this work, the novelty of this paper lies in its focus on the directly reported perceptions of income risks and how they are correlated with the realized income risks estimated from the panel data.[9]

Second, my paper is most closely related to the well-documented issue of "insurance or information" in the income risk/partial insurance literature (Pistaferri (2001), Kaufmann and Pistaferri (2009), Meghir and Pistaferri (2011), Kaplan and Violante (2010), Stoltenberg and Uhlendorff (2022)). 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. If so, this may lead to the finding of "excess smoothness" of supposedly unanticipated shocks (Flavin (1988)). My paper shares the spirit with these studies in that we all use surveyed expectations to tackle the identification problem.[10] That is, I directly use the

[8]Synthesizing various data sources, Moffitt (2020) found no such obvious trend for the same period.
[9]Koşar and Van der Klaauw (2022) is a recent exception, which documents the cross-sectional/life-cycle/business heterogeneity in perceived earning risks using SCE data.
[10]See Karahan, Mihaljevich, and Pilossoph (2017) for a similar exercise.

expectation data and explicitly control for the 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 that of others is that I directly use survey-reported income risks, which are available from density forecasts, rather than the estimated risks using the difference between expectations and realizations. An advantage of my approach is that I can directly study individual-specific risks instead of that at the group level.

Third, the paper speaks to an old but recently revived trend in the literature of studying consumption/saving behaviors in models that incorporate imperfect expectations and perceptions. For instance, Pischke (1995) explored the implications of the incomplete information about aggregate/individual income innovations by modeling agents' learning about the permanent income component as a signal extraction problem. Wang (2004) studied how such forecasting uncertainty affects consumption via precautionary saving motives. Guvenen (2007) emphasizes the role of heterogeneity in life-cycle income profiles and models' agents learning about the trend component through sequential income realizations. To reconcile low MPCs in microdata and the high MPC in the macro level, Carroll et al. (2018) introduces the information rigidity of households with learning about macro news while they are fully updated about micro news. Rozsypal and Schlafmann (2023) found that households' expectation about income exhibits an over-persistent bias. More recently, Broer et al. (2021) have incorporated information choice in a standard consumption/saving model to explore its implication for wealth inequality. My paper has a similar flavor to all these studies in that it too, emphasizes the role of perceptions. However, my work differs from those previous studies in two regards. First, it focuses on the second moment, namely income risks. Second, although most of this existing work explicitly specifies a mechanism of expectation formation that deviates from the full-information-rational-expectation benchmark, this paper advocates for disciplining the model assumptions regarding belief heterogeneity by directly using survey data, while remaining agnostic about the particular model of expectation formation that drives these perceptions. [11]

This paper is also indirectly related to the research that advocates for eliciting probabilistic beliefs to measure subjective uncertainty in economic surveys (Dominitz and Manski (1997), Manski (2004), Delavande, Giné, and McKenzie (2011), Manski (2018)), where Dominitz and Manski (1997) particularly explores the patterns of income expec-

[11] See Bhandari, Borovička, and Ho (2019) for another example of directly using survey data to discipline subjective beliefs in standard macro models.

tations based on a density survey. Despite the initial suspicion about people's ability to understand, use, and answer probabilistic questions, Bertrand and Mullainathan (2001) and others have shown respondents have the consistent ability and willingness to assign a probability (or "percent chance") to future events. Armantier et al. (2017) thoroughly discuss designing, experimenting, and implementing consumer expectation surveys to ensure the quality of responses. Broadly speaking, the advocates have argued, first, that analysts must go beyond the "revealed preference" approach and, second, the availability of survey data provides economists with direct information about agents' expectations and helps them avoid imposing arbitrary assumptions.(Manski (2004)) This insight holds for not only point forecast but also for risk/uncertainty, because for any economic decision made by a risk-averse agent, both the expectation but also the perceived risks matter a great deal.

Finally, this paper is related empirically to the literature that studies expectation formation using subjective surveys. In recent decades, a long list of theories of "expectations formation" alternative to FIRE has been developed, each of which examines how agents deviate from full-information rationality benchmarks, such as sticky expectations, noisy signal extraction, least-square learning, etc. Also, empirical work has been devoted to testing these theories comparably (Coibion and Gorodnichenko (2012), Fuhrer (2018)). Yet it is fair to say that thus far, relatively little work has been done on individual variables such as labor income, which might well be more relevant to individual economic decisions. This paper shows that understanding the patterns of beliefs about individual variables, and, in particular, mean and higher moments, is fruitful for macroeconomic modeling, especially when cross-sectional heterogeneity is involved.

2. Theoretical framework

2.1. Wage process and perceived risks

To be consistent with the survey-elicited question in SCE, I primarily focus on the wage risk. Conditional on being employed at the same job and same position, and the 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)

(1) $$w_{i,t} = z_{i,t} + e_{i,t}$$

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.[12] Or some of the literature replaces the permanent component with a stationary/persistent component in the form of an AR process.[13] The transitory component could be moderately serially correlated following a moving-average (MA) process.[14] I first proceed with the generic structure, as in Equation 1 without differentiating these various specifications. I defer that discussion to Section 4.2.

Hence, wage growth from t to $t+1$ consists of the predictable change in $z_{i,t+1}$, and the change in the stochastic component $e_{i,t}$.

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

Under the assumption of the full-information rational expectation (FIRE), all shocks realized until t are observed by the agent at time t. Therefore, the expected volatility under FIRE (with a superscript $*$), is the conditional variance of wage growth from t to $t+1$. Consider it as the FIRE benchmark of what this paper hereafter refers to as perceived risk (PR), denoted as $Var_{i,t}(\Delta w_{t+1})$ (without the superscript $*$) and directly measured in the survey.

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

The predictable changes do not enter PR. Hence, the PR is the *conditional* variance of the change in the stochastic component, $Var^{*}_{i,t}(\Delta e_{i,t+1})$. Notice that it crucially depends on the time-series nature of $e_{i,t}$.

The size of the true PR is not directly observed by economists. To estimate it, researchers usually start by obtaining an approximation of the stochastic component $e_{i,t}$, denoted as $\hat{e}_{i,t}$, by subtracting observed wage growth in panel data, $\Delta w_{i,t}$, by the approx-

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

[13] Storesletten, Telmer, and Yaron (2004), Guvenen (2007), Guvenen (2009).

[14] Meghir and Pistaferri (2004).

imated predictable change, $\Delta\hat{z}_{i,t}$, that is $\Delta\hat{e}_{i,c,t} = \Delta w_{i,c,t} - \Delta\hat{z}_{i,c,t}$. To mimic $z_{i,t}$ from the agent's point of view, $\hat{z}_{i,t}$ commonly includes factors such as age polynomials, gender, education, occupation, etc. Hence, $\hat{e}_{i,t}$ are, essentially, the residuals of the first-step wage regression controlling for a limited number of observable variables measured in the panel data. Then, the cross-sectional variance of $\Delta\hat{e}_{i,t}$ is the input for estimating income risks. It is usually referred to as the "volatility" in the literature. [15]

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

Note that the common practice usually estimates income risks at the group level, denoted as c (such as age, education, cohort, etc), although in theory, the risk as perceived by a FIRE agent could be totally individual-specific. That is so because, at the individual level, there are no realizations of risks, but a particular draw of shock. (Equation 4) The within-group cross-sectional variation of a sufficiently large group size is needed for such an estimation.

Unlike the PR of the agent, $Var_c(\Delta\hat{e}_{i,c,t})$ 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. Two important issues affect 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[16] agent at time t. That is so primarily because econometricians with the panel data of earnings cannot control for other "unobserved heterogeneity" not measured in the data. This is equivalent to the "superior information" problem, [17] which refers to the possibility that agents have advance information regarding their wage growth, and this information is not available to econometricians. For instance, a worker might be concerned that a recent dispute with her boss may negatively affect her wage next year, but econometricians have no way of knowing this.

Second, the comparison is sensitive to the time-series nature of $e_{i,c,t}$. Again, this occurs because economists' estimated volatility is unconditional, while the perception is conditional on the information until time t. To illustrate this point, imagine a very

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

[16] 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.

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

persistent component in the income shock. Under the aforementioned process, the estimated income volatility also includes the variance of the realized shock until t, which has already entered the information set of the agent. Therefore, even if the econometricians perfectly recover the $e_{i,t}$ in the first-step regression, the presence of a persistent component in income changes would result in differences between PR and estimated 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 unconditional variance, typically by assuming a particular time-series structure of the stochastic component e and using cross-sectional moments restrictions to estimate its size. I return to this discussion in Section 4.2.

To summarize, for two reasons, survey-elicited PR has an invaluable use and is preferable to conventional income risk estimation based on cross-sectional realizations, which is also used to parameterize macro models. First, survey-reported PR is, by construction, conditional on the information set of each agent i, which is likely to include intrinsic heterogeneity specific to the individual or the advance information useful to forecasting that individual's own wage growth.[18] Economists who try to approximate the PR cannot do as well as the agents who answer the questions, because the latter's 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 when they estimate group-specific income risks, by grouping individuals on the basis of very limited dimensions of observable factors, such as education and age.

It is worth pointing out that despite these advantages, survey-implied PRs may reflect the risk perceptions of agents subject to certain behavioral biases, such as overconfidence, in contrast to those assumed by FIRE. I explore below the robustness of the model results of the paper with respect to these alternative assumptions. The key takeaway is that even if the survey-implied PRs don't align with the true objective size of income risks, they prove to be a better input for predicting individual decisions than the calibrated income risks as done in the conventional approach.

3. Data, variables and density estimation

[18]For the same reason, the literature on partial insurance uses expectational surveys to resolve the superior information problem. See Pistaferri (2001), Kaufmann and Pistaferri (2009) and others for examples.

3.1. Data on perceived risks

The data used for this paper were obtained 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 during the period June 2013 to July 2021, or 97 months.

I primarily rely upon the density forecast of individual earnings by each respondent in the survey to estimate perceived income risks. The main question used is framed as follows: "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%?".[19] Then, I fit the bin-based density forecast in each survey response with a parametric distribution.[20] The variance of the estimated distribution naturally represents an individual-specific perceived risk. To obtain the wage risk in real terms, I further add the individual-specific inflation uncertainty estimated by the same procedure and use the same individual's density forecasts of inflation in SCE. This procedure is predicated on the assumption that agents regard individual wage growth and aggregate inflation as independent random variables. This assumption is not perfect. For the robustness of the results, I use both adjusted PR in real terms and nominal PR for the empirical results below.

Crucially, because 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 risk, and this has two important implications.

First, focusing on the wage risks avoids the problem of misconstruing earning changes due to voluntary labor supply decisions as risks. Empirical work estimating income risks is often based on data from total earnings or even household income, in which voluntary labor supply decisions inevitably confound the true degree of uninsured idiosyncratic risks. This survey-based measure used here is not subject to this problem. Second, the wage risk also excludes important sources of income fluctuations, such

[19] In the online survey, 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, which is crucial for any further analysis.

[20] This follows the approach employed by Engelberg, Manski, and Williams (2009) and researchers in the New York Fed (Armantier et al. (2017)). Appendix A.1 documents in detail the estimation methodology and its robustness.

as unemployment and job switching. As demonstrated by research (e.g., Low, Meghir, and Pistaferri (2010)), major job transitions often are the dominant source of income risks individual workers face. I separately examine unemployment risk expectations, surveyed as perceived job-separation and finding probabilities in SCE, in Section 4.4.[21]

3.2. Wage data

I examine longitudinal data on individual labor earnings from the 2014-2017 and 2018-2020 panels of the Survey of Income and Program Participation (SIPP).[22] Each panel of SIPP, which surveys approximately 1000-2000 workers, is designed to be a nationally representative sample of the U.S. population. The interviews, conducted once a year, collect data on individuals' monthly earnings, hours of work, and other labor market outcomes.[23] On average, each individual is surveyed for 33 months over multiple waves of the survey.

For the purpose of this paper, using SIPP to estimate wage risk has obvious advantages over other commonly used datasets, the most notable of which is the Panel Study of Income Dynamics (PSID). SIPP contains information that allows me to work with wage changes conditional on staying at the same job with the same employer, thanks to its detailed records of job transitions and a unique employer identifier. In contrast, PSID only provides biennial records of labor earnings 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 on macroeconomic conditions.

To ensure the comparability between the perceptions and realized outcomes, I obtain the hourly wage of workers employed by the same employer by dividing the total monthly earnings from the *primary job* by the average hours of work for the same job for only those who stay with the same employer for at least 2 years. To identify job stayers,

[21] Closely related to this, Caplin et al. (2023) elicits subjective job transition probabilities and unconditional earning distributions for each scenario of job transitions. They are enabled to combine these into a holistic income distribution. Unlike them, I separately explore wage distribution conditional on staying in the same job and job transition probabilities.

[22] Other recent work that estimates income risks using SIPP includes Bayer et al. (2019), who, in contrast to this paper, use quarterly total household income rather than the monthly job-specific earning of individuals.

[23] This causes the "seam" issue documented by Moore (2008), which states that reported changes in answers (e.g. wage growth) within survey waves are systematically smaller than cross-wave changes. For the baseline estimation, I exclude the cross-wave earning growth, which produces a lower-bound estimate of wage risks. See Appendix A.3 for more inspection of this issue.

I follow the same approach by Low, Meghir, and Pistaferri (2010) and I impose five criteria. I only include (1) the working-age population between 25-65; (2) private-sector jobs, excluding workers from government or other public sectors; (3) the same job as the last year; (4) monthly wage rates that are no greater than 10 times or smaller than 0.1 times of the average wage; (5)those who don't have days away from work during the reference month without the pay. This leaves me with a monthly panel of 350-1000 individual earners for the sample period 2013m3-2019m12. Appendix A.3 discusses in greater details the data selection procedure and reports summary statistics.

4. Basic facts about perceived income risks

4.1. Observable and unobservable heterogeneity in PRs

In both income risk estimation and parameterization of the incomplete market macro models, it is common practice to assume, first, that idiosyncratic risks differ as a function of certain observable factors such as education, gender, and age, and second, there is no additional within-group heterogeneity in the degree of the risk.[24] This section reports my 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 can be 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 PRs (both in real and nominal terms), approximated wage volatility, $Var_c(\Delta\hat{e}_{i,t+1})$, as defined in Equation 4, and the calibrated risk $Var_{i,t}(\Delta\hat{e}_{i,t+1})$ based on estimation of a specified wage process (see the next section for the exact procedure of generating it) by age, gender and education. Regarding the education profile of wage risk, both wage volatility and calibrated risks are higher for more educated workers. This is consistent with the finding of Meghir and Pistaferri (2004), who examine total labor income instead of wage. In contrast, risk perceptions exhibit the opposite pattern with respect to education level: less-educated workers report higher PRs than more-educated workers. Regarding the life-cycle pattern of risks, neither wage volatility nor estimated risks show a monotone pattern over the life

[24]For instance, Meghir and Pistaferri (2004) found that more educated workers face higher income risks than the less educated ones. 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. In their models, Cagetti (2003), Blundell, Pistaferri, and Preston (2008), and Carroll et al. (2017) allowed for heterogeneous risks across different demographic variables.

cycle.[25] In contrast, perceived risks almost monotonically decline over the life cycle for both males and females. These findings are confirmed in Table 1, which reports the group average of PR, wage volatility and estimated risks.

The second salient fact is that PR is, in always *smaller* than wage volatility and, in most of the time, smaller than calibrated wage risks. In particular, the volatility of year-over-year wage growth is well above 30% and calibrated risk of different groups fall in the range of 5-15% per year (in standard deviation term). The latter estimates land in the lower range compared to the estimates in a large literature and those further used in models, as summarized in Table A.3.[27] In contrast, the average perceived risks reported in the survey are only about 3-4%, and at least 50% smaller. For instance, a male high school graduate on average perceives his annual wage risk to be 4 percentage points in terms of standard deviation, while the calibrated risk of the same group is above 9-10%, not to mention a substantially greater wage volatility of 40%.

Such a size difference is also evident in the Figure 2, which plots the distribution of PRs against the distribution of individual-level annual wage volatility in SIPP that can be explained by observable demographic variables such as age, gender and education. This corresponds to our wage volatility $Var_c(\Delta\hat{e}_{i,t+1})$ where each group c is an particular individual. The figure shows that PRs are concentrated at a much lower range of values around (2-4%), while in contrast, the average predicted size of wage volatility falls in the range of 10-20%.

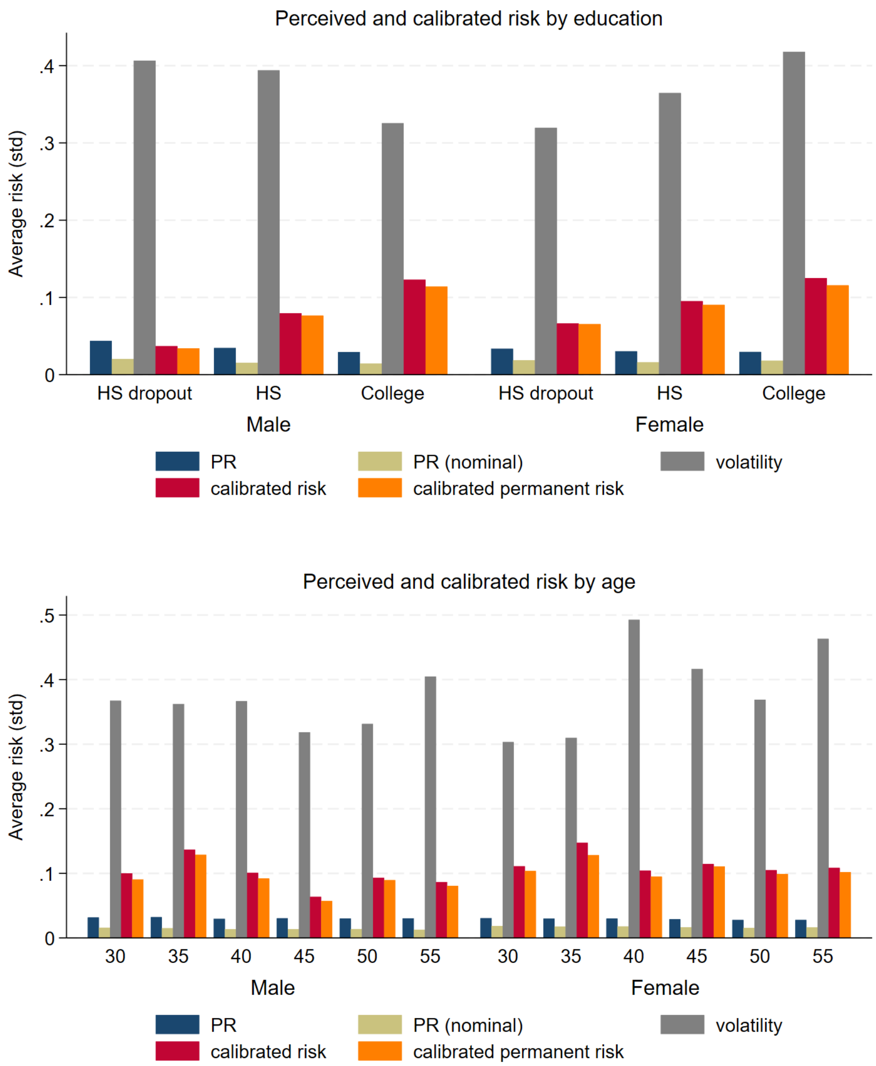
Another finding in addition to the size difference is that PRs are more heterogeneous than that of the wage volatility that can be explained by observable factors. This can be confirmed by observing in Figure 2 that the dispersion of PRs is significantly larger than that of the explainable dispersion of individual volatility. Consistent with this, the R^2 of a regression of PR on all observable factors in SCE, without individual fixed effects, is at most 10%, while including fixed effects increases R^2 to 70%.[28] This finding has two implications. First, the role of within-group heterogeneity suggests that the

[25]The homogeneous age pattern of wage risks is not necessarily contradictory with the well documented declining pattern estimated using data on household income or total earning[26]. 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.

[27]The most comparable estimates in the literature are by Low, Meghir, and Pistaferri (2010), as it explicitly estimates the wage risk of job stayers separately from job switching and unemployment spells. The authors report annual permanent and transitory risk of 10%, respectively. This implies a total risk of approximately 35%-40%.

[28]Appendix A.2.1 plots the distribution of unexplained residuals of PRs, expected wage growth and higher-order perceived risks such as skewness after controlling for observable individual characteristics, including age, age polynomial, gender, education, type of work, and time fixed effects. All of them show sizable within-group heterogeneity.

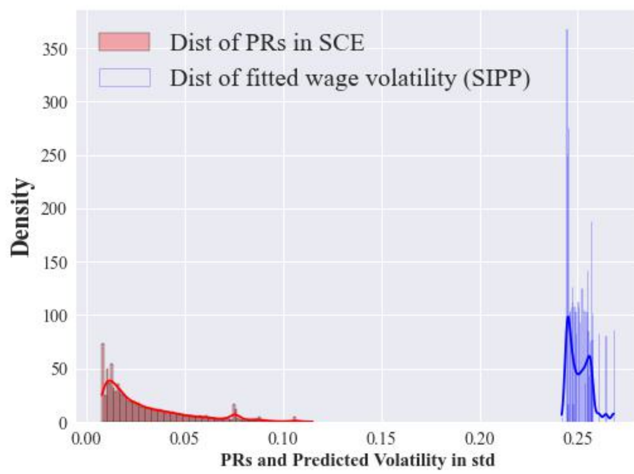
FIGURE 1. Perceived Risks, Wage Volatility and Calibrated Wage Risks by Observable Factors



Note: Real and nominal perceived risk (from SCE), average estimated wage volatility (from SIPP), estimated/calibrated 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 calibrated risk is equal to the estimated risk of the permanent and transitory component of wage, based on the process specified in Equation 5.

conventional practice of estimating and modeling income risks as only differing by demographic dimensions has limitations. Second, heterogeneity in PR can be directly put into use to model heterogeneous income risks without identifying the source of heterogeneity. Therefore, in Section 5, my model calibration adopts such an approach.

FIGURE 2. Dispersion in Perceived Wage Risks



Note: Distributions of PRs regarding real wage growth in SCF and individual wage volatility explained by age, age polynomials, gender, education, and time fixed effects.

4.2. Decomposed risks of different persistence

As previewed in Section 2, a crucial aspect of income risk estimation is the time-series nature of the shocks. A realized permanent/persistent shock contains information about future wage, while an entirely transitory shock does not. Therefore, in the two scenarios, agents perceive different degrees of risk. This is crucial to making an fair comparison between survey-reported PRs and the calibrated risks using conventional methods.

To proceed, I adopt a commonly used income/wage process in a large body of literature.[29] I specify that the stochastic component $e_{i,t}$ consists of a permanent component p that follows a random walk and a transitory component θ that is i.i.d. The shocks to both

[29] MaCurdy (1982), Abowd and Card (1989), Gottschalk et al. (1994), Carroll and Samwick (1997), Blundell, Pistaferri, and Preston (2008), etc. Crawley, Holm, and Tretvoll (2022) presents a more parsimonious process to resolve the possible model misspecification caused by "time-aggregation" problem.

components are log-normally distributed, with mean zero and potentially time-varying variances σ^2_{ψ} and σ^2_{θ}.[30]

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

Under this specific wage process, the PRs of an FIRE agent are equal to the summation of the variance of the two components $Var^*_{i,t}(\Delta e_{i,t+1}) = \sigma^2_{\psi,t} + \sigma^2_{\theta,t}$. But, in contrast, the wage volatility estimated from panel data provided that the change in predictable component Δz is perfectly controlled for as in Equation 4, is a sample analog of $Var(\Delta e_{i,t}) = \sigma^2_{\psi,t} + \sigma^2_{\theta,t-1} + \sigma^2_{\theta,t}$. It differs from the PR by $\sigma^2_{\theta,t-1}$, exactly due to its unconditional nature. The intuition here is that the variance of the transitory shock that realized at time $t-1$ is no longer perceived as wage growth risk conditionally at time t.

Therefore, a more comparable counterpart of PR from indirect calibration is the sum of *estimates of* permanent and transitory risks, $Var_t(\Delta \hat{e}_{i,t}) = \hat{\sigma}^2_{\psi} + \hat{\sigma}^2_{\theta}$. Denote it as $\widehat{PR}$ and it will be referred to as "calibrated risks" from now on. To do so, I follow the same GMM estimation procedure in the literature [31] to identify the time-averaged variances of the permanent and transitory component of the monthly wage growth using SIPP's wage data for the same period. Then I convert these monthly risk parameters into annual frequency to be comparable to perceived risks about annual wage growth.[32]

Table 1 reports the group-specific estimates of total, permanent, and transitory wage risks based on wage panel data in comparison with the average and median perceived risks of the same group. The main finding from this comparison is that within each group, the perceived risks (PRs) are systematically lower than indirectly estimated risks (Calibrated Risks), even if the latter is at least one step closer to the perceived risk compared to the unconditional wage volatility. In addition, Figure A.3 in the Appendix compares the two, allowing for time-variation of the risks. The size difference and negligible correlation across time between PRs and calibrated risks remain.

The most likely explanation for this disconnect in both size and time-varying patterns

[30] This also corresponds to the model specification as in Equation 11.

[31] See Appendix A.4.1 for details. The estimation procedure follows Abowd and Card (1989), Carroll and Samwick (1997), Meghir and Pistaferri (2004), and Blundell, Pistaferri, and Preston (2008), which have minor differences depending on the model specification.

[32] For the permanent component, the annual risk is the summation of monthly permanent risks over the next 12 months. The transitory risk in annual frequency, in contrast, is the average of monthly risks over the next 12 months. Appendix A.4.3 provides alternative estimates for quarterly and yearly frequency.

TABLE 1. Perceived Risk, Volatility and Calibrated Risks by Group

	PR(mean)	PR(median)	Volatility	CalibratedRisk	PermanentRisk	TransitoryRisk
Gender						
Male (50%)	0.031	0.024	0.356	0.103	0.097	0.0226
Female (49%)	0.03	0.024	0.397	0.113	0.106	0.027
Education						
HS dropout (0%)	0.036	0.021	0.359	0.052	0.05	0.0067
HS graduate (40%)	0.032	0.024	0.38	0.087	0.083	0.016
College/above (58%)	0.029	0.023	0.373	0.124	0.115	0.0311
5-year age						
20 (2%)	0.038	0.032	0.382	0.069	0.068	0.0063
25 (12%)	0.033	0.028	0.359	0.135	0.132	0.0107
30 (13%)	0.031	0.025	0.338	0.104	0.096	0.0245
35 (14%)	0.031	0.024	0.338	0.141	0.128	0.0476
40 (13%)	0.03	0.023	0.433	0.102	0.093	0.0302
45 (14%)	0.029	0.022	0.37	0.09	0.085	0.0195
50 (14%)	0.029	0.021	0.351	0.099	0.095	0.0188
55 (15%)	0.029	0.02	0.434	0.098	0.092	0.023
Total (100%)	0.03	0.023	0.376	0.108	0.101	0.0248

Note: This table reports the mean and median PRs ($Var_{i,t}(\Delta w_{i,t+1})$), estimated annual wage volatility ($Var_c(\Delta w_{i,t+1})$), calibrated risks ($\hat{\sigma}^2_{\psi} + \hat{\sigma}^2_{\theta}$), and the risks of permanent ($\hat{\sigma}^2_{\psi}$)and transitory ($\hat{\sigma}^2_{\theta}$) wage components for different groups. Note that they are all expressed in standard deviation units.

between the two series is either unobservable heterogeneity or superior information, a point I will formally elaborate in the next section. For the common panel-data-based estimation to correctly identify idiosyncratic wage risks relevant to heterogeneous individuals, two requirements need to be satisfied. First, economists need to perfectly exclude the predictable changes in wage growth from the point of the agent, by both correctly approximating $z_{i,t}$ in the first-step regression, and by correctly decomposing various components' variance contained in $e_{i,t}$. Second, they also need to correctly assume the dimensions by which risks differ across individuals. Given the stringency of these requirements, directly reported PRs may provide a better alternative to calibrating income risks that are truly relevant from the point of view of heterogeneous individuals.

4.3. Accounting for the evidence

This section proceeds with the baseline explanation for the size differences between survey-based PRs and calibrated risks using panel data: the role of unobserved heterogeneity. In the model section 6, I explore alternative hypotheses, such as misperception of risks by agents because of behavioral biases.

For simplicity, I follow the same wage process specified in Equation 5 but assume away time-variation of risk parameters. Furthermore, all agents have individual-specific permanent $\sigma^2_{i,\psi}$ and transitory risks $\sigma^2_{i,\theta}$. This is to assume that there is generally heterogeneity in perceived risks across individuals.

To capture unobserved heterogeneity (or advance information) explicitly, I allow for the change in unexplained wage residual $\Delta\hat{e}_{i,t}$ based on only a small set of observables to be different from what is truly unpredictable from the individual i's point of view, $\Delta e_{i,t}$, by exactly $\xi_{i,t}$. (Equation 6) To be entirely consistent with the time series nature of $e_{i,t}$ in the wage process, I also assume that $\xi_{i,t}$ consists of a corresponding permanent component $\xi^{\psi}_{i,t}$ and a *change* in the transitory component $\Delta\xi^{\theta}_{i,t}$.[33]

A good example of $\xi^{\psi}_{i,t}$, namely the individual-specific expected innovation to the permanent wage, is the wage rise expected by a fresh Ph.D. graduate who will start a professor job next year. An example of $\Delta\xi^{\theta}_{i,t}$, an expected transitory change yet unlikely unobservable by researchers is the future income cut to a professor expecting to be on sabbatical leave for one semester.

$$
\begin{aligned}
\Delta\hat{e}_{i,t} &= \Delta e_{i,t} + \xi_{i,t} \\
&= \psi_{i,t} + \Delta\theta_{i,t} + \xi_{i,t} \\
&= \psi_{i,t} + \Delta\theta_{i,t} + \xi^{\psi}_{i,t} + \Delta\xi^{\theta}_{i,t}
\end{aligned} \tag{6}
$$

When economists estimate wage risks using panel data, they typically identify the *average* permanent and transitory risks at the population or group level. 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 general-methods-of-moment (GMM) estimation used 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.[34] The intuitive reason for this is that $\psi_{i,t}$ and $\xi^{\psi}_{i,t}$, observable or not by economists, have the exactly same statistic properties. The same can be said for the transitory components.

[33] This is similar to the specification of unobserved heterogeneity in *income* as in Primiceri and Van Rens (2009), which only allows for a permanent component of the unobserved heterogeneity.

[34] Essentially, the estimated transitory risk with is equal to the size of $\hat{\sigma}^2_{\theta} = -cov(\Delta\hat{e}_{i,t}, \Delta\hat{e}_{i,t+1}) = -cov(\Delta e_{i,t} + \xi_{i,t}, \Delta e_{i,t+1} + \xi_{i,t+1}) = -\int cov(\Delta e_{i,t} + \xi_{i,t}, \Delta e_{i,t+1} + \xi_{i,t+1}) di = \int \sigma^2_{i,\theta} di + \sigma^2_{\xi,\theta}$, and an estimated permanent risk of $\hat{\sigma}^2_{\psi} = var(\Delta\hat{e}_{i,t}) - 2\hat{\sigma}^2_{\theta} = var(\Delta e_{i,t}) + (\sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta}) - 2\hat{\sigma}^2_{\theta} = \int var(\Delta e_{i,t}) di + (\sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta}) - 2\hat{\sigma}^2_{\theta} = \int (\sigma^2_{i,\psi} + 2\sigma^2_{i,\theta}) di + (\sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta}) - 2\hat{\sigma}^2_{\theta} = \int (\sigma^2_{i,\psi} + 2\sigma^2_{i,\theta}) di + \sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta} - 2(\int \sigma^2_{i,\theta} + \sigma^2_{\xi,\theta}) = \int \sigma^2_{i,\psi} + \sigma^2_{\xi,\psi}$.

$$\widehat{\text{PR}} = \hat{\sigma}^2_{\psi} + \hat{\sigma}^2_{\theta} = \int \text{PR}_i di + \sigma^2_{\xi} = \int \sigma^2_{i,\psi} di + \int \sigma^2_{i,\theta} di + \underbrace{\sigma^2_{\xi,\psi} + \sigma^2_{\xi,\theta}}_{\text{unobserved heterogeneity}} \tag{7}$$

Therefore, the 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 in SCE and what is the average estimated risk ($\hat{\sigma}^2_{\psi} + \hat{\sigma}^2_{\theta}$) using panel data (the difference between the two vertical lines in Figure 3).

Furthermore, with an auxiliary assumption that the two unobserved terms of all individuals have the same ratio κ, we can further decompose the estimated heterogeneity into $\sigma^2_{\xi,\psi}$, and $\sigma^2_{\xi,\theta}$, which represents the size of unobserved heterogeneity in permanent and transitory wage changes, respectively.

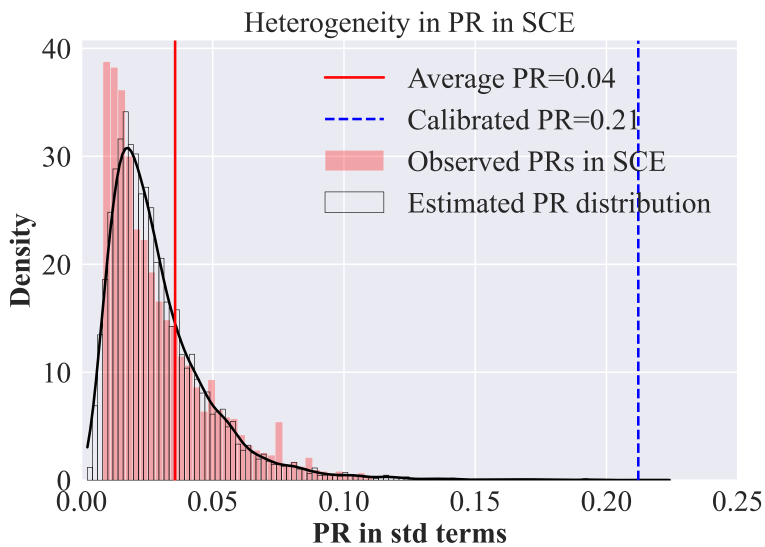
In addition, to directly identify the heterogeneity in PRs, I assume individual *PR*s follow a log-normal distribution with mean μ_{PR} and standard deviation σ_{PR}.

$$\log(\text{PR}_i) \sim N(\mu_{\text{PR}}, \sigma^2_{\text{PR}}) \tag{8}$$

The two parameters can be straightforwardly estimated by fitting a truncated log-normal distribution to the cross-sectional distribution of the time-average PRs in SCE, as shown in Figure 3.

With the benchmark wage risk estimates of $\sigma_{\psi} = 0.15$ and $\sigma_{\psi} = 0.15$ (used to calibrate the baseline model in Section 5), hence a conventionally calibrated $\widehat{PR} = 0.41$, and $\kappa = 1$, the procedure produces the estimated unobserved heterogeneity: $\sigma_{\xi,\psi} = 0.13$ and $\sigma_{\xi,\theta} = 0.13$, and a fitted truncated-log-normal distribution of PRs, as plotted in Figure 3. In Section 5, I use these estimates to calibrate the heterogeneous perceived wage risks in the model. Using the wage risk estimates by Low, Meghir, and Pistaferri (2010), $\sigma_{\psi} = 0.10$ and $\sigma_{\psi} = 0.09$ yield a smaller estimate of the unobserved heterogeneity $\sigma_{\xi,\psi} = 0.08$, $\sigma_{\xi,\theta} = 0.07$. In both cases, the estimates imply that a dominant fraction of observed wage inequality and volatility is attributed to to unobserved heterogeneity, instead of risks, as the conventional calibration of the model. This is on the basis of the assumption PRs truly reflect the degree of risks agents face.

FIGURE 3. Estimated Heterogeneity in PRs



Note: The observed distribution of perceived income risks from SCE and the fitted truncated log-normal distribution estimation.

4.4. Unemployment risk perceptions

My analysis has so far focused only on wage risks conditional on staying in the same job. But it only constitutes a part of the income risks, given that major labor market transitions, such as job loss and switching, usually result in more significant changes in labor income.[35] In addition, unemployment risks are usually another central input of the incomplete-market macroeconomic models.[36] In these models, as in the approach to wage risks, the common practice is to model the process of labor market transitions on the basis of externally estimated stochastic processes.[37]. This section shows that, although, on average, the survey-reported expectations of job separation/finding probabilities track realized aggregate dynamics computed through panel data in a standard approach in search & match labor literature, as in Fujita and Ramey (2009), it masks a huge amount of heterogeneity, which is not assumed in standard models.

[35] Low, Meghir, and Pistaferri (2010), Davis and Von Wachter (2011).

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

[37] The exceptions are models that endogenize job search & matching mechanisms, such as Krusell, Mukoyama, and Şahin (2010), Ravn and Sterk (2017), Ravn and Sterk (2021), McKay (2017) in which job-separation rates typically remains exogenous and externally calibrated.

To achieve a fair comparison between perceptions and realizations measured for different horizons, I cast both probabilities into a continuous-time rate for a Poisson point process. [38] Figure 4 plots the converted realizations of job-separation/finding rates, respectively, against the corresponding average, and the 25/75 percentile of the expectations across all survey respondents at each point in time. A number of straightforward findings emerge. First, although the two series are constructed independently of one another, on average, perceptions track the aggregate realizations relatively well. The most notable deviation between the belief and realization occurred during March 2020, which saw an unprecedented increase in one-month job separations[39] and a dramatic decrease in job findings. Second, however, as shown by the wide 25/75 interrange-percentile around mean expectations, individual respondents vastly disagree on their individual separation and finding probabilities. Because the question in the survey concerns the individual-specific transitions, it is reasonable to assume that this reflects either the unobserved heterogeneity or information available to their individual status, which economists cannot directly observe.

4.5. Perceived income risk and consumption spending

Due to precautionary saving motives, higher perceived risks induce households to lower current consumption, thus increasing expected consumption growth. Despite such a clear directional prediction in theory, identifying the exact size of such an effect(i.e., perceived risks on ex-ante consumption/saving decisions that are separate from the ex-post income impacts) has been challenging when conventional data sources are used as it does not directly elicit ex-ante plans and perceptions at the individual level. This section shows that the coexistence of individual-specific perceived risks and the consumption plan of the same individual in SCE provides a rare opportunity to resolve this problem.[40] This contrasts with the best practice to date, which is to impute ex-

[38] Assuming the reported probability of separation 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 is $-log(1-P_{i,t}(u_{t+12}|e_t))/12$. This follows from the fact that for a continuous-time Poisson point process with an event rate of θ, the arrival probability over a period of Δt units of time is equal to $1-exp^{-\theta\Delta t}$. With the realized month-to-month flow rate estimated from CPS $P(ue_{t+1}|e_t)$, the corresponding realized Poisson rate is $-log(1-P(ue_{t+1}|e_t))$.

[39] The observation of March 2020 was dropped in the graph, otherwise, it overshadows all other observations in the sample.

[40] Guiso, Jappelli, and Terlizzese (1992) was an early example of directly testing precautionary saving motives using reported subjective income risks of Italian households. Other recent works that examine the impacts of expectations on readiness to spend include Bachmann, Berg, and Sims (2015) and Coibion et al. (2020). Recently, in closely related studies, Fuster, Kaplan, and Zafar (2020) and Bunn et al. (2018)

FIGURE 4. Expected and Realized Job-separation/finding Rate

Note: realized job separation/finding rates are computed from CPS following the method of Fujita and Ramey (2009). Both realizations and perceived probabilities are expressed as Poisson point rates in continuous time, with one month as the unit of time. 3-month moving average of each series is plotted.

---

have relied on survey answers to measure stated marginal propensity to consume. The most related to this paper, Christelis et al. (2020) also finds that expected consumption growths are positively correlated ante unemployment risks to a particular individual on the basis of only a number of observable factors from realizations (Harmenberg and Öberg 2021).

I run a regression of expected consumption growth reported in SCE by each repondent on the same individual's expected wage growth, perceived wage and unemployment risks under a range of specifications.

$$E_{i,t}(\Delta c_{i,t+1}) = u_0 + u_1 E_{i,t}(\Delta w_{i,t}) + u_2 \text{Var}_{i,t}(\Delta w_{i,t+1}) + \xi_{i,t}$$

In the past, the literature took it for granted that such a reduced-form regression has a clear correspondence to the commonly used approximated Euler Equation to the second-order (for instance, Parker and Preston (2005)), where the expected consumption growth is equal to the sum of intertemporal substitution and the precautionary saving motive. But a linearly approximated Euler equation is reasonable only under a set of unrealistic and stringent assumptions, such as the absence of external borrowing constraint, the absence of the buffer-stock-saving behavior as elaborated in Carroll and Samwick (1997), and mild-sized income fluctuations, a point forcefully made by Carroll (2001) and Ludvigson and Paxson (2001). Therefore, in the regression results below, I primarily focus on testing the significance and the qualitative effects of precautionary saving motives, without providing a structural interpretation of the size of the estimated coefficient.

Across all specifications, as reported in Table 2, in addition to the significantly positive coefficient of expected wage growth, which is consistent with the buffer-stock-saving behavior, perceived risk is positively correlated with the expected spending growth, as the precautionary saving motive predicts. Specifically, after controlling for individual fixed effect (e.g., the discount rate), and time fixed effect (e.g., interest rate), each unit increase in perceived variance leads to around a 1.7 percentage point increase in expected spending growth. Additionally, for the same individual, the perceived unemployment probability, measured by perceived job separation probability, in the next 4 months also has a significantly positive correlation with expected consumption growth. [41]

with perceived income risks at the individual level based on Dutch households.

[41] 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 expected spending growth is indeed positively correlated with perceived risks, taking into account the bias, it implies that the correlation between the two is greater.

TABLE 2. Perceived income risks and the household spending plan

	(1)	(2)	(3)	(4)	(5)
expected wage growth	0.324***	0.306***	0.254***	0.243***	
	(0.0825)	(0.0828)	(0.0334)	(0.0334)	
perceived wage risk	6.127***	6.185***	2.096***	1.711***	
	(1.163)	(1.165)	(0.439)	(0.442)	
perceived UE risk next 4m					0.353***
					(0.0553)
R-squared	0.000939	0.00318	0.953	0.953	0.633
Sample Size	56046	56046	56046	56046	6269
Time FE	No	Yes	No	Yes	Yes
Individual FE	No	No	Yes	Yes	Yes

Regression results of expected spending growth on perceived income risks. Standard errors are clustered by household. *** p<0.001, ** p<0.01 and * p<0.05.

5. Perceived risks and wealth inequality

Section 4.5 provides assuring evidence that individual consumption/saving decisions are indeed correlated with *their own* income expectations and perceived risks, regardless of the correctness of such perceptions. In this section, I show that recalibrating income risks based on reported perceptions in a standard incomplete-market macro model also generates more empirically plausible predictions regarding inequality in liquid wealth, compared to the indirect calibrations, and the difference is quantitatively important.

5.1. An overlapping-generation model

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

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_τ at the work-age of τ. After retiring at the age of T, the agent lives for other $L - T$ periods of life and receives social security benefits. Without aggregate risks, there is no need to treat calendar time t and the working age τ as two separate state variables, hence I suppress time script t from now on. All shocks are idiosyncratic.

5.1.1. Consumer's problem

The consumer chooses the entire future consumption path to maximize expected life-long utility under a discount factor β and potentially age-dependent survival probabilities $1 - D$.

$$\max \quad \mathbb{E}\left[\sum_{\tau=1}^{\tau=L}(1-D)^{\tau-1}\beta^{\tau-1}u(c_{i,\tau}) + (1-D)^{L-1}\beta^{L-1}u(a_{i,L})\right] \tag{9}$$

where $c_{i,\tau}$ represents consumption at the work-age of τ. The felicity function $u(c)$ takes a standard CRRA form with a relative risk aversion coefficient of ρ: $u(c) = \frac{c^{1-\rho}}{1-\rho}$. The second term is the homothetic bequest motive from the last period of life, derived from the post-consumption asset $a_{i,L-1}$.

Denote total cash in hand at the beginning of the period τ as $m_{i,\tau}$, the end-of-period saving in period τ after consumption as $a_{i,\tau}$, and the bank balance at the beginning of the period τ as $b_{i,\tau}$. Labor income y_τ is taxed at an income tax rate of λ and social security tax rate λ_{SS}. 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 constraints.

$$\begin{aligned}
a_{i,\tau} &= m_{i,\tau} - c_{i,\tau} \\
b_{i,\tau+1} &= a_{i,\tau}R \\
m_{i,\tau+1} &= b_{i,\tau+1} + (1-\lambda)(1-\lambda_{SS})\, y_{i,\tau+1} \\
a_{i,\tau} &\geq 0
\end{aligned} \tag{10}$$

The last inequality above is the no-borrowing constraint.

5.1.2. Income process

Each agent receives stochastic labor income during her working age from $\tau = 0$ to $\tau = T$ and receives a social security benefit after retirement. The income processes in both sub-periods can be defined in a generic manner as described below. By allowing the possibility of persistent unemployment spells, the process is assumed to follow a slight variant of the standard permanent/transitory income process used in the literature[42]. Specifically, $y_{i,\tau}$ is a multiplication of the idiosyncratic wage rate[43] $w_{i,\tau}$ 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 forces of general equilibrium.

$$
\begin{aligned}
y_{i,\tau} &= exp(w_{i,\tau})W \\
exp(w_{i,\tau}) &= exp(p_{i,\tau})\xi_{i,\tau}
\end{aligned} \tag{11}
$$

During the work, the permanent wage component is subject to a shock $\psi_{i,\tau}$ in each period and grows at a deterministic life-cycle profile governed by $\{G_\tau\}_{\tau=1...L}$.

$$
exp(p_{i,\tau}) = G_\tau exp(p_{i,\tau-1})exp(\psi_{i,\tau}) \tag{12}
$$

The persistent/transitory shock $\xi_{i,\tau}$ takes different values depending on status of employment.

$$
\xi_{i,\tau} = \begin{cases} exp(\theta_{i,\tau}) & \text{if} \quad \nu_{i,\tau} = e \quad \& \quad \tau \leq T \\ \zeta & \text{if} \quad \nu_{i,\tau} = u \quad \& \quad \tau \leq T \\ \mathbb{S} & \text{if} \quad \tau > T \end{cases} \tag{13}
$$

where ζ is the replacement ratio of the unemployment insurance and $\theta_{i,\tau}$ is the i.i.d. mean-zero shock to the transitory component of the wage conditional on staying employed.

Notice that this process also embodies the income process after retirement after $\tau = T$. The agent receives social security with a replacement ratio $\mathbb{S}$, and proportional to her permanent wage and aggregate wage rate. That is, the effective pension benefit received is $\mathbb{S}p_{i,\tau}W$. I assume that the permanent component after retirement follows a deterministic path without additional stochastic shocks.

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

[43] This is equivalent to the usual interpretation of it in the literature as idiosyncratic productivity under the implicit assumption of a perfectly inelastic labor supply.

Parameters governing the degree of income risks during working age ($\tau < T$) in this model consist of the standard deviations of the permanent and transitory wage shocks σ^2_ψ and σ^2_θ, respectively, as as well as the transition probabilities of job spells. For both type of wage shocks, we assume standard normal distribution.[44]

$$
\begin{aligned}
\psi_{i,\tau} &\sim N(-\frac{\sigma^2_\psi}{2}, \sigma^2_\psi) \\
\theta_{i,\tau} &\sim N(-\frac{\sigma^2_\theta}{2}, \sigma^2_\theta)
\end{aligned}
\tag{14}
$$

The transition matrix between unemployment ($\nu_{i,\tau} = u$) and employment ($\nu_{i,\tau} = e$) is the following.[45]

$$
\pi(\nu_{\tau+1}|\nu_\tau) = \begin{bmatrix} \mho & 1-\mho \\ 1-E & E \end{bmatrix}
\tag{15}
$$

In general, this assumption implies to some degree that unemployment risks persist, but it conveniently nests the special case in which 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 that is unemployed and employed at each age, denoted by $\Pi^{\mho}_\tau$ and Π^{E}_τ, respectively, are essentially deterministic and are not dependent on age.

It is worth pointing out that I assume that all parameters of income risks σ_ψ, σ_θ, $\mho$, and E are age-invariant. Doing this allows me to avoid restricting the heterogeneity in income risks only by the dimension of age.

5.1.3. Value function and consumption policy

The following two value functions characterize the consumer's problem in the last period of life ($\tau = L$) and all the earlier periods ($\tau < L$), respectively.

[44] The means of the normal distributions are adjusted so that the exponential have a mean of one.

[45] This formulation follows Krueger, Mitman, and Perri (2016).

$$V_\tau(\nu_{i,\tau}, m_{i,\tau}, p_{i,\tau}) = \max_{\{c_{i,\tau},a_{i,\tau}\}} \quad u(c_{i,\tau}) + u(a_{i,\tau}) \tag{16}$$

$$V_\tau(\nu_{i,\tau}, m_{i,\tau}, p_{i,\tau}) = \max_{\{c_{i,\tau},a_{i,\tau}\}} \quad u(c_{i,\tau}) + (1-D)\beta\mathbb{E}_\tau\left[V_{\tau+1}(\nu_{i,\tau}, m_{i,\tau+1}, p_{i,\tau+1})\right] \tag{17}$$

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 a purely transitory unemployment shock ($\mho = 1 - E$).[46]

The solution to the stated problem above is a set of age-specific optimal consumption policies, $c^*_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau})$, and the saving policies, $a^*_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau})$. Both are functions 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.

$$Y = ZK^\alpha N^{1-\alpha} \tag{18}$$

The capital depreciates at a rate of δ each period. The factors of input markets are fully competitive.

5.1.5. Demographics

The population growth rate is n. With a deterministic life-cycle profile of survival probabilities, there exists a stable age distribution $\{\mu_\tau\}_{\mu=1,2,..L}$ such that $\mu_{\tau+1} = \frac{(1-D)}{1+n}\mu_\tau$ 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.[47]

[46] Relying on the homotheticity of the value function, one can reduce the number of state variables by normalizing the value function by permanent income level p_τ, so that it drops from the state variable. I also use the endogenous grid method (EGM) developed by Carroll (2006).

[47] With 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

The government runs a balanced budget in each period. Therefore, outlays from unemployment insurance are financed by the income tax that is levied on both labor income and unemployment benefits. Given a replacement ratio ζ and the proportion of employed population $1 - \Pi^{\mho}$, the corresponding tax rate λ can be easily pinned down on the basis of the equation below. [48]

$$\lambda \left[1 - \Pi^{\mho} + \zeta \Pi^{\mho}\right] = \zeta \Pi^{\mho} \tag{19}$$

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

$$\lambda_{SS} \sum_{\tau=1}^{T} \mu_\tau G_\tau (1 - \Pi^{\mho}) = \mathbb{S} \sum_{\tau=T+1}^{L} \mu_\tau G_\tau \tag{20}$$

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 τ and their idiosyncratic state x. The former is given by $\{\mu_\tau\}_{\tau=1,2,..L}$. For the latter, $\psi_\tau(B)$ is used to represent the fraction of agents at age τ whose individual states lie in B as a proportion of all age τ agents. The distribution of age $\tau = 1$ agents depends 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.

$$\psi_\tau(B) = \int_{x \in X} P(x, \tau - 1, B) d\psi_{\tau-1} \quad \text{for all} \quad B \in B(X) \tag{21}$$

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

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

of income shocks.[49]

In the absence of the aggregate risk, I focus on the stationary equilibrium of the economy (StE), which consists of consumption and saving policies $c(x,\tau)$, $a(x,\tau)$, as well as constant production factor prices, including the real interest rate R and the wage W, the initial wealth of newborn b_1, unemployment benefit ζ, tax rate λ, 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, and the tax rate λ.

$$\begin{aligned} c(x,\tau) &= c^*(x,\tau) \\ a(x,\tau) &= a^*(x,\tau) \end{aligned} \tag{22}$$

2. Distributions $(\psi_1, \psi_2, \ldots, \psi_L)$ are consistent with optimizing behaviors of household, as described in Equation 21.

3. The factor markets are clearing.

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

4. Firm optimization under competitive factor markets.

$$\begin{aligned} W &= Z(1-\alpha)(K/N)^{\alpha} \\ R &= 1 + Z\alpha(K/N)^{\alpha-1} - \delta \end{aligned} \tag{24}$$

5. The initial bank balance of newborns is equal to accidental bequests.

$$b_1 = \sum_{\tau} \mu_\tau D \int_{x\in X} a(x,\tau) R d\psi_\tau \tag{25}$$

[49] In the model computation, the P functions correspond to age-specific transition matrices over a finite number of discretized grid points of multiple state variables. The age-specific distributions $\psi_\tau(B)$ are generated by forward iteration of multiplying the distribution of age $\tau-1$ by the transition matrix of age τ.

6. The government budget is balanced as described in Equation 19 and 20.

The economy may potentially arrive at different stationary equilibrium, depending on the specific assumptions about the size and heterogeneous income risks, which in this model, include σ_ψ, σ_θ, E, and $\mho$.

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 detail.

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

Regarding the deterministic permanent income profile over the life-cycle, G_τ, I draw on an age polynomial regression of the wage growth from SIPP for workers aged 25-65 while controlling for other observable demographic variables such as education, gender, occupation, and time fixed effects, etc.[50] This yields estimation results very similar to those obtained by Gourinchas and Parker (2002), Cagetti (2003) and Kaplan and Violante (2014). The estimated wage profile is plotted in Appendix A.5. For the retirement phase, I assume a one-time drop of 20% in permanent wage at age 66, i.e. $G_{41} = 0.8$, and then the permanent wage stays flat till death. This produces an average expected growth factor of permanent wage over the entire life exactly equal to one. This serves as a normalization. Note that although alternative assumptions, such as a smoother decline of income after retirement, do change the wealth distribution across generations among the retired, they do not change consumption/saving decisions because such a profile is entirely deterministic.

Initial conditions. Assumptions about the cross-sectional distribution of the initial permanent productivity and liquid asset holdings matter for the subsequent wealth inequality. I set the standard deviation of the log-normally-distributed initial permanent wage $p_{i,\tau}$ to be 0.6 in order to match the heterogeneity in "usual income" (an approximation of the permanent income) at age 25 from the SCF. Initial liquid assets holdings at $\tau = 0$ are 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 1), I thoroughly

[50]The deterministic profile generated from SCF using the same procedure is steeper, possibly because labor income from multiple jobs is used.

survey the risk estimates used in the existing incomplete market macro literature, as summarized in Table A.3 in the Appendix. For comparison, I convert all risks into the annual frequency (because some of the estimates are for a different frequency). Whenever group-specific risks are assumed (depending on education and age), I summarize them as a range. Also, for models that assume a persistent instead of a permanent component, I treat the assumed size of the persistent risks as a lower bound for the permanent risk.[51] 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 employed in the paper.

Regardless of the disagreement in these estimates, the income risks used in these models are constantly larger than those reported in the survey. This is true for presumably the most comparable one to the surveyed PR among them, the wage risk estimate by Low, Meghir, and Pistaferri (2010). I use the median values of each parameter in the literature as the benchmark income risks profile, which is a combination of $\sigma_\psi = 0.15$, $\sigma_\theta = 0.15$. And following the calibration of Krueger, Mitman, and Perri (2016), the yearly probability of staying on unemployment is $\mho = 0.18$ and that of staying employed $E = 0.96$.

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. As in Krueger, Mitman, and Perri (2016), unemployment insurance replacement ratio is set to be $\mu = 0.15$. 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 wage 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 that finance unemployment insurance and social security are determined by the equilibrium within the model.

Preference. The coefficient of relative risk aversion ρ is 2. The discount factor β is set to be 0.96 for partial equilibrium and 0.98 for general equilibrium experiments. A higher β helps generate a higher wealth-to-income ratio to be consistent with the assumption that savings in GE correspond to a broad definition of wealth. I deliberately choose to fix

[51] 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.

the two preference parameters using consensus values instead of internally calibrating them to match moments such as mean or median wealth/income ratio in SCF.[52]

Table 3 summarizes the parameters used in the calibration of the baseline model. This is nearly identical to what would be considered as a standard calibration of an incomplete market liquid-assets calibration. (Kaplan and Violante (2022))

TABLE 3. Model Parameters

block	parameter name	values	source
risk	σ_ψ	0.15	Median estimate from the literature
risk	σ_θ	0.15	Median estimate from the literature
risk	$U2U$	0.18	Median estimate from the literature
risk	$E2E$	0.96	Median estimate from the literature
initial condition	$\sigma_\psi^{\text{init}}$	0.629	Estimated for age 25 in 2016 SCF
initial condition	bequest ratio	0	assumption
life cycle	n	0.005	U.S. census
life cycle	T	40	standard assumption
life cycle	L	60	standard assumption
life cycle	$1-D$	0.994	standard assumption
preference	ρ	2	standard calibration
preference	β	0.96/0.98	standard calibrations
policy	$\mathbb{S}$	0.65	U.S. average
policy	λ	N/A	endogenously determined
policy	λ_{SS}	N/A	endogenously determined
policy	μ	0.15	U.S. average
production	W	1	target values in steady state
production	K2Y ratio	3	target values in steady state
production	α	0.33	standard assumption
production	δ	0.025	standard assumption

Parameters used in the baseline model. All parameters, whenever relevant, are at the annual frequency.

6. Model results

[52]Kaplan and Violante (2022) discusses in detail how the internally calibrated discount factors in one-asset models differ depending on targeting liquid wealth or total net worth. Their calibration of β is 0.945 for a targeted liquid-asset-to-income ratio of 0.6 and 0.98 for a targeted net-worth-to-income ratio of 4.6. This is the same as the average value estimated in the models with heterogeneous time preferences, as in Carroll et al. (2017) and Krueger, Mitman, and Perri (2016).

6.1. Baseline model

I first examine the patterns of wealth accumulation and inequality generated from a benchmark calibration, as reported above. In particular, under a set of standard parameterization on permanent and transitory wage risks at the annual frequency to be $\sigma_\psi = 0.15$ and $\sigma_\theta = 0.15$, and the unemployment risks to be $U2U = 0.18$ and $E2E = 0.96$, the baseline of Figure 5 reproduces the well-known result[53] that a carefully calibrated standard one-asset incomplete market model without additional heterogeneity, such as that in time discount rates, predicts less wealth inequality (a Gini coefficient of 0.63 in partial and 0.64 in general equilibrium) than that in the liquid wealth inequality in the data. For instance, the distribution of net liquid wealth based on the definition of Kaplan, Violante, and Weidner (2014) and Carroll et al. (2017) [54] has a Gini coefficient of 0.88 in the 2016 SCF.[55]

The second major discrepancy between the model and data is that the former significantly underpredicts the share of agents who are close to borrowing constraints. In particular, the baseline model predicts a share of hands-to-month households (H2M) (defined as agents whose ratios of wealth to annual permanent income are below 1/24) less than 1%, which is significantly lower than 0.31, the share computed based on net liquid wealth in SCF. It is known that the strong precautionary saving motives in this model incentivize agents to build saving buffers and stay away from their borrowing constraints.

The baseline model also generates a hump-shaped average wealth over the life cycle resembling the patterns of net liquid wealth (for PE) and net worth (for GE) seen in SCF. (Figure 5) In particular, allowing the voluntary bequest in the last period of life helps me match the saving behaviors after retirement better.

6.2. Model results with perceived risks

In this section, I sequentially add the following three features of PRs, and show that it increases the wealth Gini and the fraction of H2M from the baseline model, which are

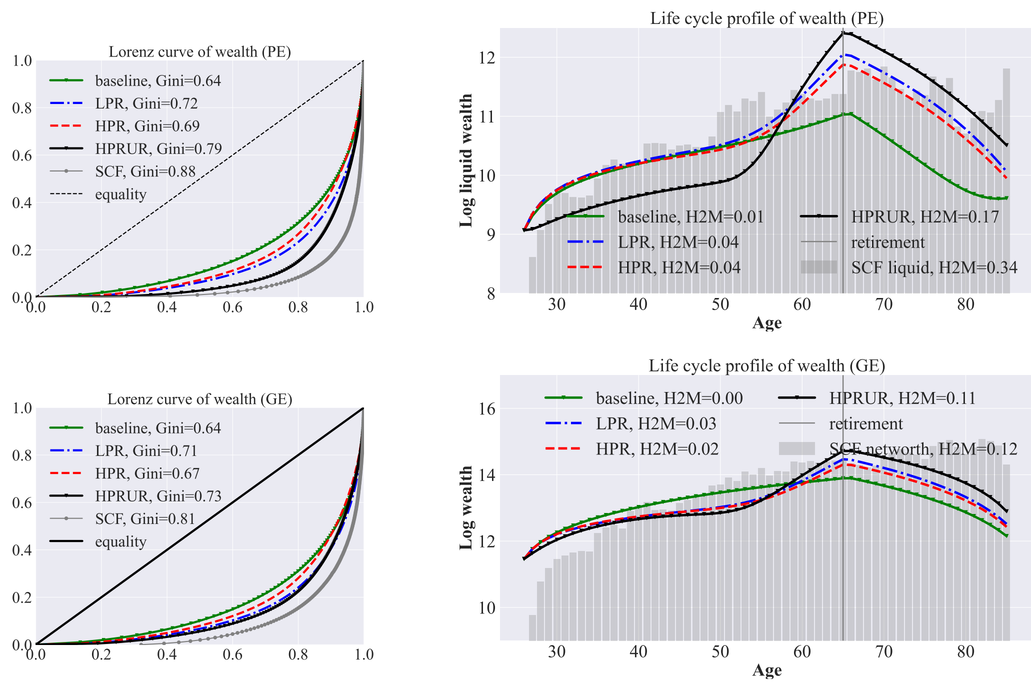
[53] See Guvenen (2011), De Nardi (2015), and Kaplan and Violante (2018) for a thorough survey on this topic.

[54] According to this definition, the liquid asset includes checking, saving, money market funds, government bonds, directly held mutual funds, stocks and corporate bonds, and liquid debt is the sum of all credit card balances that accrue interest, after the most recent payment.

[55] I exclude the households in SCF with negative net liquid wealth and the top 5% in terms of total net worth. The former is meant to be consistent with the no-borrowing constraint assumption. The latter is also a common practice in the literature (for instance, Kaplan and Violante (2022)) because the one-asset model has been found to poorly explain the consumption/saving behaviors of the super-rich.

closer to that observed in the data. First is an average lower wage risk (*LPR*). The second is heterogeneous perceived wage risks in addition to the average lower size (*HPR*). The third is heterogeneous unemployment risks (*HPRUR*) as revealed in perceived U2U and E2E probabilities.

FIGURE 5. Wealth Inequality in Partial and General Equilibrium: A Model Comparison



Note: the upper 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 partial equilibrium. The bottom panel shows the same figures in the general equilibrium, with the total net worth in SCF as the measure of household wealth.

6.2.1. Lower wage risks (LPR)

For LPR calibration, I keep everything the same as in the baseline calibration above except for two inter-dependent changes. First, I make the permanent and transitory risks smaller on the basis of the average perceived risk of 0.04, i.e. $\sigma_{\psi} = 0.03$ and $\sigma_{\theta} = 0.03$. In the meantime, I calibrate in the heterogeneity in growth rates of wage anticipated by the agents using the estimates of $\sigma_{\xi,\psi}$ and $\sigma_{\xi,\theta}$ produced in Section 4.3.

In practice, this means including three equally probable distinctive deterministic wage profiles to be consistent with a conservative lower bound of yearly permanent heterogeneity $\sigma_{\xi,\psi} = 0.04$. Intuitively, it means every year in life cycle, a dispersion of 4 percentage points standard deviation of permanent wage growth across agents are anticipated by agents. The profiles are plotted in Figure A.8. The mean profile corresponds to the baseline model calibration of $\{G_\tau\}_{\tau=1...L}$.

This reconfiguration of the relative importance of risks and heterogeneity is crucial to ensure comparability with the baseline model. Lower perceived risks and higher predictable heterogeneity are the flip sides of the same coin. Other things equal, a smaller size of wage risks would have mechanically lowered realized wage/income inequality in the model. For the model to still admit realistic wage inequality as seen in the data like SIPP, the differences between the baseline calibration of risks and the lower risks need to be attributed to unobserved heterogeneity in wage growth rates.

The LPR in Figure 5 shows two implications of a smaller size of risks and a larger role of anticipated heterogeneity. First, a lower PR induces a milder precautionary saving motive and reduces buffer-stock savings of all working agents, as indicated by a lower level of wealth-to-income ratio than in the baseline model. This also results in a slightly larger fraction of H2M agents (3% in both PE and GE) compared to nearly zero in the baseline model.

Second, allowing for a larger role in heterogeneity instead of risks unambiguously leads to *more* wealth inequality than in the baseline model (A Gini coefficient of 0.72 in PE and 0.71 in GE), as shown in Figure 5. This is 7 percentage point increase in the Gini compared to the baseline.

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 that different individuals face beyond common observable factors. Hence, I directly calibrate the heterogeneity in wage risks using the estimated distribution of PRs in Section 4.3.

I use three equally probable values [0.01, 0.02, 0.04] for σ_ψ and σ_θ, which are discretized from the estimated log-normal distribution of *PRs* to calibrate such heterogeneity. On top of *LPR*, allowing heterogeneity in PRs unambiguously contributes to more wealth inequality because it induces different precautionary saving motives and buffer stock savings. But this is counteracted by the existence of agents facing nearly no wage risks, which objectively induces less income and wealth inequality, as discussed in *LPR*. As a result of the two competing forces, the wealth Gini coefficients in *HPR* actually decrease by 3-4 percentage points from *LPR*, but they both remain significantly higher than the baseline.

A recalibration in both *LPR* and *HPR* scenarios do take the baseline model closer to matching the data, but it is worth noting that the improvements in model performance are not sufficiently large. This is particularly so when it comes to matching the size of H2M agents. It suggests that only incorporating heterogeneity in wage risks can be complemented by recalibrating another important source of heterogeneity, namely the unemployment risks.

6.2.3. Heterogeneous unemployment risks (HPRUR)

Just like the calibration of wage risks, a common calibration strategy of incomplete market models with unemployment spells typically parameterizes the model with one homogeneous pair of $U2U$ ($\mho$ in the model) and $E2E$ (E in the model) probabilities (e.g., Krueger, Mitman, and Perri (2016)). But this assumption 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)).

To capture the heterogeneity in unemployment risks, I adopt the same approach as in Section 4.3 applied to perceived wage risks to fit a truncated log-normal distribution to the survey-reported perceived U2U and E2E probabilities (See Figure A.9). 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 $E2E$. According to these profiles, approximately one-third of the agents in the economy face no risks of persistent unemployment spells either through high job-finding rates or nearly zero job separation rates. Meanwhile, one-third of the agents face a potentially long duration of unemployment with a lower expected income and a higher probability of hitting borrowing constraints.

The resulting model, which has both heterogeneous wage risks and unemployment risks (*HPRUR*), unsurprisingly, generates a significantly higher degree of wealth inequality (an increase of 10 percentage points in Gini coefficient to 0.79 in PE. Interestingly, the increase in GE is not as significant as in PE, but it is still 6 percentage points higher than in *HPR*. In addition, allowing for a sensible degree of ex-ante heterogeneity in unemployment risks across the entire population stably increases the fraction of H2M agents. Approximately 17% agents fall into the category in PE and 11% in GE. It turns out the mean liquid-wealth-to-income ratio *HPRUR* equal to 0.70, although not targeted, is also brought closer to the value in SCF 0.67.

With the incremental improvement of the model fit, it is natural to ask about the relative importance of various patterns of PRs. Table 4 summarizes all model-implied measures and their empirical counterparts. The summary suggests the relative importance of wage growth rates and unemployment risks depends on the measures of fit. First, heterogeneous wage growth rates (in conjunction with a lower wage risk) and heterogeneous unemployment risks, play an equally important role in explaining wealth inequality. The two channels increase with Gini by about 8-10 percentage points, respectively. Second, it is the heterogeneity in unemployment risks instead of wage growth, that helps produce a more realistic share of H2M agents.

It is also worth asking where in the wealth distribution contributes the most to the results in the model experiments. This is not obvious, ex-ante, because a wider wealth distribution could come from a relatively higher share of the rich or a lower share of the poor. The location-specific wealth shares in Table 4 suggest the latter mechanism. In particular, from the baseline model to *HPRUR*, the wealth share of the bottom half of the agents in the economy reduces by 7 percentage points. In contrast, the 40% wealthier agents in the economy, altogether, reduce their wealth share by an equal amount. This implies that the wider wealth distribution is primarily driven by a leftward expansion to borrowing constraints, which is also consistent with a higher share of H2M agents.

6.2.4. The role of preference heterogeneity

One of the common additional features added to the baseline model in the existing literature to match the empirical wealth inequality is heterogeneity in preferences, especially in time discount rates.(Krusell and Smith (1998), Krueger, Mitman, and Perri (2016), Carroll et al. (2017).) Such a modeling assumption has been recently supported by some empirical evidence and laboratory experiments.[56] Despite such indirect evidence, however, the exact degree of time preference heterogeneity in the model cannot be directly observed and estimated. Thus, the literature commonly adopts the "revealed preference" approach to indirectly calibrate the model-implied heterogeneity in preferences to match the data.

Compared to preference heterogeneity, survey-implied heterogeneity in perceptions has the advantage of being directly observable and useful in the model. This paper

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

Table 4. Summary of Model Results and Data

Model/Data	Gini	Bottom 0.9	Bottom 0.7	Bottom 0.5	Wealth/income	H2M share
SCF (liquid)	0.88	0.18	0.04	0.01	0.67	0.34
baseline (PE)	0.64	0.47	0.22	0.10	1.17	0.01
LPR (PE)	0.72	0.40	0.15	0.06	1.06	0.04
HPR (PE)	0.69	0.45	0.17	0.07	1.03	0.04
HPRUR (PE)	0.79	0.33	0.08	0.03	0.70	0.17
SHPRUR (PE)	0.81	0.29	0.08	0.03	0.78	0.16
SCF (net worth)	0.81	0.29	0.09	0.02	6.72	0.12
baseline (GE)	0.64	0.47	0.22	0.10	2.17	0.00
LPR (GE)	0.71	0.41	0.15	0.07	1.20	0.03
HPR (GE)	0.67	0.46	0.18	0.08	1.23	0.02
HPRUR (GE)	0.73	0.41	0.14	0.06	1.12	0.11
SHPRUR (GE)	0.76	0.35	0.12	0.05	1.22	0.10

Note: model-implied Gini coefficients, the wealth shares owned by the bottom 90, 70 and 50 percent of the agents, mean wealth-to-income ratio, and shares of hand-to-mouth agents (H2M), in the stationary distribution of partial and general equilibrium. H2M is defined as those whose liquid wealth is no more than two weeks of(1/24 of annual) income. The same statistics in the data are computed for both net liquid wealth, and total net worth using 2016 SCF.

shows that 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 (not explored in this paper), is that disciplining the model with observed heterogeneity, such as in income risks perceived by agents, makes the model more transparent and allows welfare analysis to be carried out with greater clarity than in the unobserved preference heterogeneity approach.

It would have been a straightforward exercise for this paper to quantitatively compare the estimated preference heterogeneity from the baseline model and the preferred model that additionally accounts for the observable heterogeneity in income risks. As shown in Table 4, an incremental recalibration of the baseline model gradually reduces the model residuals in comparison with the data. So it should be no surprise that the indirectly estimated preference heterogeneity will be less.

6.3. Subjective perceived risks

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

But it is critical to consider how robust the results are if we adopt a different assumption that agents' perceived 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).

More accurately speaking, in the subjective model, the following transition probabilities of the distribution of agents over state spaces, $\tilde{P}()$, corresponding to the $P()$ in the objective model in Equation 21, is now both a function of individual consumption/saving policies based on subjective risks and the objective income risks that determine the realization of income shocks and distribution of income.

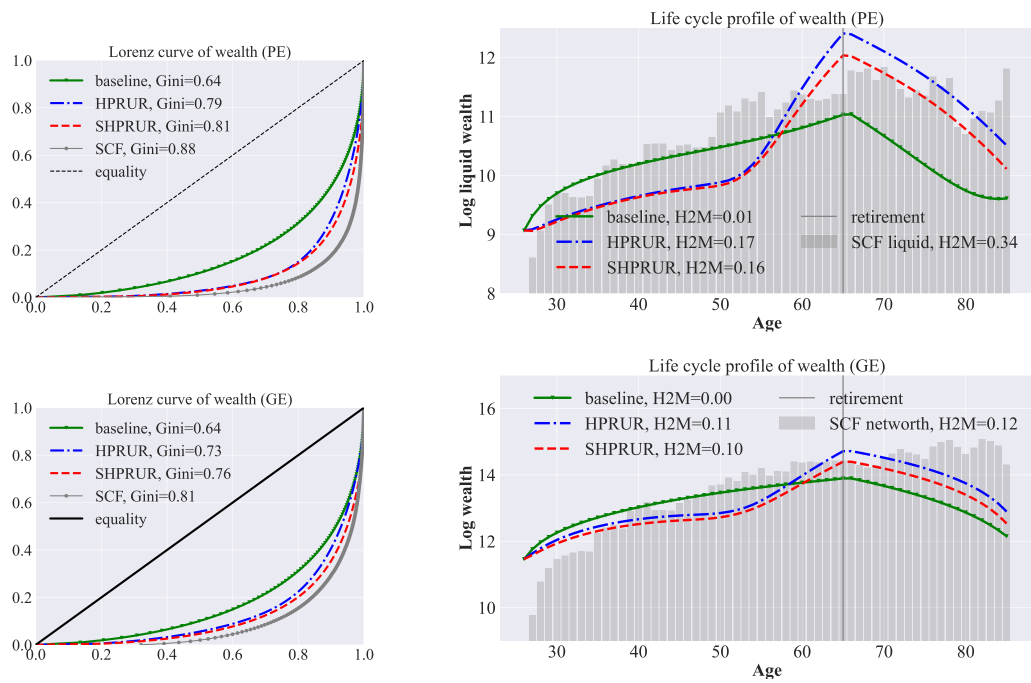
$$\tilde{\psi}_\tau(\tilde{B}) = \int_{\tilde{x}\in\tilde{X}} \tilde{P}(\tilde{x}, \tau-1, \tilde{B})d\tilde{\psi}_{\tau-1} \quad \text{for all} \quad \tilde{B} \in \tilde{B}(X) \tag{26}$$

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 because it is via ex-ante consumption/saving decisions of the agents based on certain perceived income risks. The second channel can be called the "outcome" channel because it is a function of the ex-post realized dispersion of income shocks.

Figure 6 compares the subjective model *SHPRUR* with both the baseline and the *HPRUR* model as calibrated above. The subjective model shifts the Lorenz curve further outward (a Gini of 0.81 in PE and 0.76 in GE) relative to the baseline model, and the shift is greater than in the objective model. Such a shift only comes from changes in ex-ante saving behaviors when a heterogeneous and lower income risk profile is added to the baseline model. Meanwhile, the fraction of H2M agents, 16% in PE and 10% in GE, remain similar to the objective model. The minor difference between the subjective and objective model lines suggests that it is mainly the "choice" channel, instead of realized inequality via the "outcome" channel, that drives the results. Even if we don't recalibrate the objective income risks in the baseline model, but, instead, allow the survey-implied risks to serve as a better input when predicting consumption/saving choices, it reduces the difference in wealth inequality unexplained between the model and data.

To summarize, the subjective model results reinforce the key argument of this paper: even if the perceived income risks reported in the survey are not perfectly "correct" compared to what objectively governs the size of stochastic income shocks, to the extent that household saving decisions are made based on such perceptions, they generate model predictions about wealth accumulation behaviors which are better aligned with the data.

FIGURE 6. Wealth Inequality in Partial and General Equilibrium: Objective v.s. Subjective



Note: the upper panel shows, under objective (*HPRUR*) and subjective assumptions (*SHPRUR*), 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. The bottom panel shows the same figures in the general equilibrium, with the total net worth of SCF as the measure of household wealth.

7. Conclusion

A large class of incomplete-market macroeconomic models that features uninsured idiosyncratic income risks and resulting wealth inequality does not incorporate one observable dimension of heterogeneity in income risks. Utilizing the New York Fed's *Survey of Consumer Expectations* which elicits density forecasts of wage growth and job transition probabilities, I explore the model implications of two major empirical findings. The survey-reported perceived risks are more heterogeneous than that is assumed by common calibration of these models, and prove to be another observable factor useful for matching the model-predicted wealth inequality with empirical patterns. Furthermore, perceived risks are lower than the conventional estimates/ calibration, suggesting a higher degree of anticipated heterogeneity, which helps explain why these models usually predict higher buffer stock savings than in the actual data.

This paper demonstrates the rich potential of incorporating into heterogeneous-agent models survey data that reflects realistic heterogeneity in expectations/perceptions. In a world that offers increasingly available survey data that directly measures expectations, economists no longer are obligated to calibrate important model parameters such as income risks indirectly from the panel data and adopt the stringent assumption of rational expectations. The use of survey-implied heterogeneity establishes a direct link between expectations and behaviors and helps economists match empirical patterns within the macroeconomy better.

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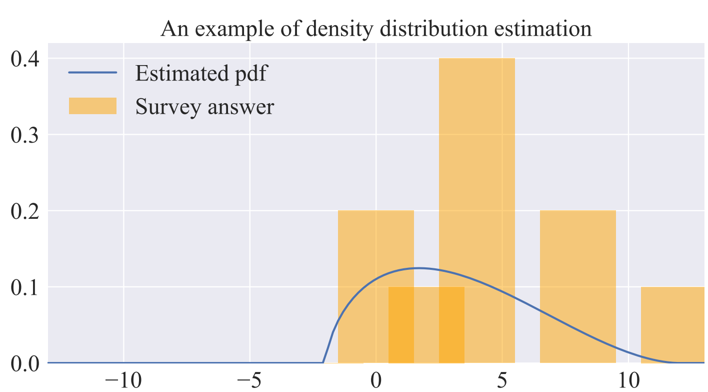
Appendix A. Online Appendix

A.1. Density estimation of survey answers

With the histogram answers for each individual in hand, I follow Engelberg, Manski, and Williams (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.

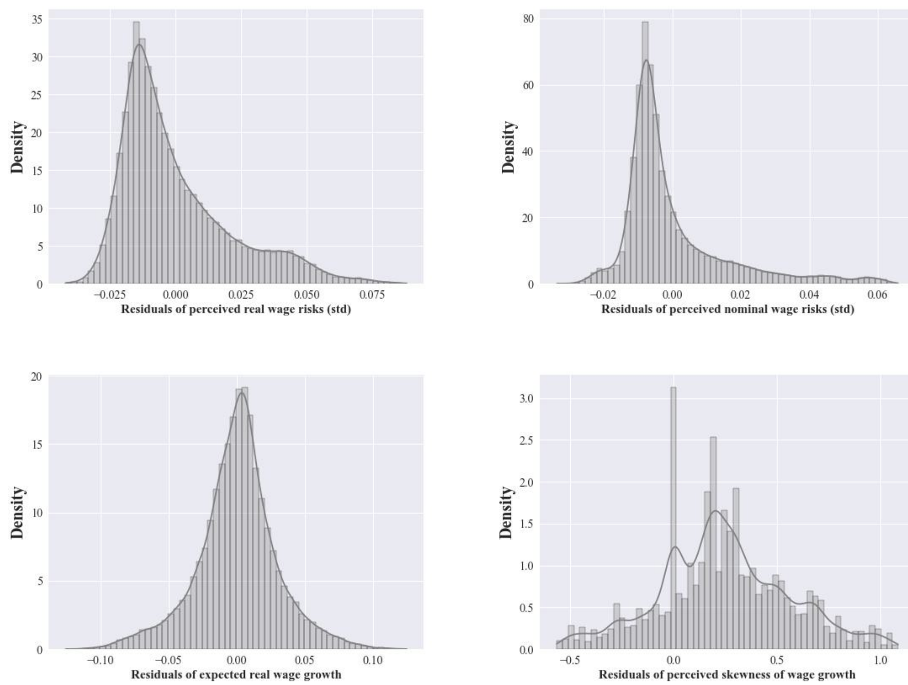
FIGURE A.1. An illustration of the density estimation of the survey answer



Note: This is one example of the bin-based forecast of wage growth in 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

FIGURE A.2. Dispersion in Expected Wage Growth and Perceived Skewness



Note: The distributions of residuals of nominal PR (in standard deviation terms), expected nominal and real wage growth rates, and perceived skewness of 1-year-ahead wage growth in SCE unexplained by observable demographic variables.

analysis, I exclude top and bottom 1% observations, leading to a sample size of around 53,180.

A.2. Other facts about PR

A.2.1. Heterogeneity of expectations in other moments

Figure A.2 shows the within-group heterogeneity of real PRs, nominal PRs, expected real wage growth rates, and perceived skewness controlling for observable demographic variables in SCE.

A.2.2. Time-varying patterns of PRs

Figure A.3 plots the time-varying 1-year-ahead perceived risks and corresponding calibrated risks of the total, permanent and transitory wage components, based on the estimates of SIPP data. Under correct model specification and FIRE of the agents, one may expect the PRs and estimated risk to be, if not equal, at least comove with each other. But the results suggest a negligible correlation between the two series. It is also obvious that the magnitudes of the PRs are significantly lower than the estimated risk using SIPP, reinforcing the finding in Section 4.1. For instance, the latter, which is based on the full sample, should be 10% in standard deviation a year, while the average earning risk perception in *SCE* is only 2%.

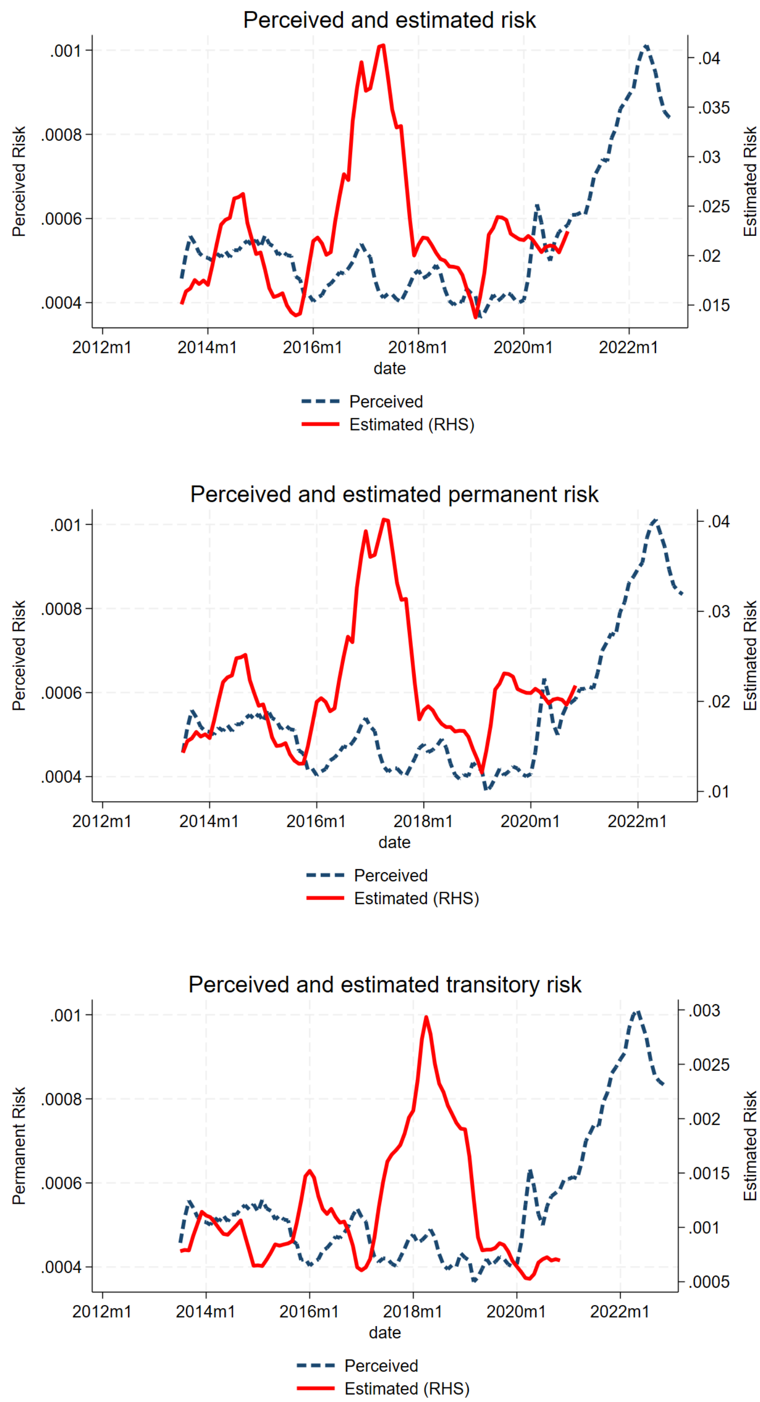
A.3. Wage risk estimation using SIPP data

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 are listed as below, and it is approximately identical to that in Low, Meghir, and Pistaferri (2010) for computing the wage rate of the same job using 1993 panel of SIPP.

- Time: January 2013-December 2020
- Age: 20 - 60
- 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.

FIGURE A.3. Perceived versus Calibrated Risks over Time



Note: Median 1-year-ahead perceived wage risks (in variance terms) in the whole SCE sample against the estimated total, permanent, and transitory risks over the *same* period. Both series concern real wage growth. The realized risks are first estimated monthly from SIPP and then aggregated into annual frequency.

- Drop imputed values: EINTTYPE==1 or 2.
- Drop government/agriculture jobs: drop if TJB1_IND>=9400.

Based on the selected sample, Table A.1 reports the size and approximated group-specific wage volatility as defined in Equation 4.

TABLE A.1. Summary statistics of SIPP sample

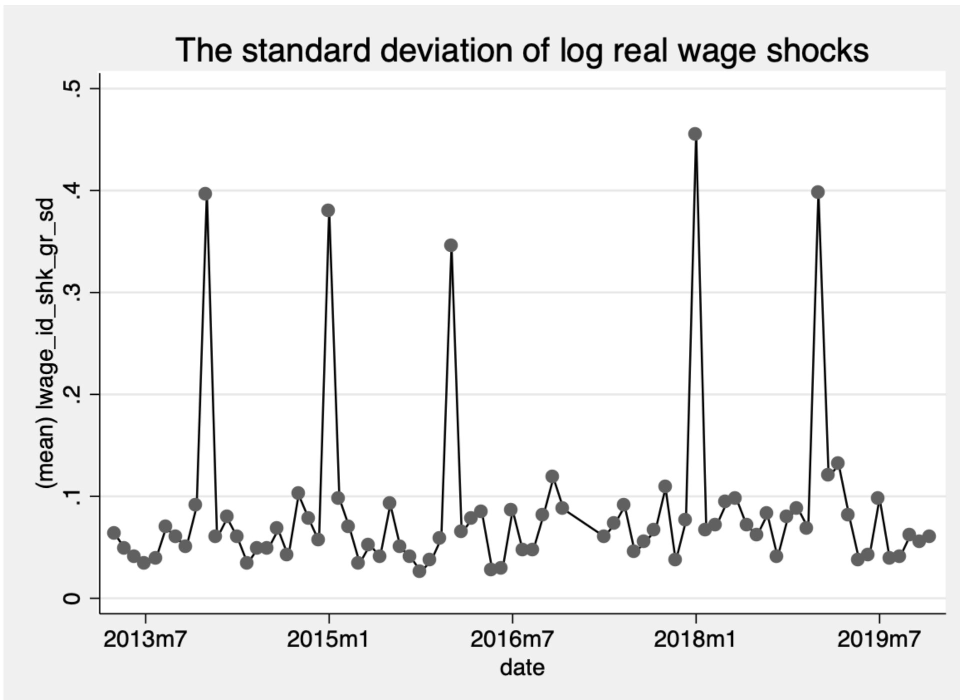
	Obs	Volatility
Year		
2013 (14%)	9,278	N/A
2014 (16%)	12,011	0.41
2015 (12%)	8,853	0.37
2016 (8%)	5,699	0.34
2017 (9%)	6,305	N/A
2018 (11%)	7,877	0.45
2019 (11%)	8,047	0.37
2020 (10%)	7,131	0.35
2021 (4%)	2,974	0.42
Education		
HS dropout (21%)	14,900	0.39
HS graduate (45%)	31,345	0.39
College/above (33%)	21,930	0.39
Gender		
male (56%)	38,181	0.38
female (43%)	29,994	0.4
Total (100%)	68,175	0.39

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, Conrad, and Fricker 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.4, where there is always a spike in the size of volatility between December to January in the sample period.[57]

FIGURE A.4. Estimated monthly wage volatility



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

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

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

the quarterly/yearly period such that it covers the cross-wave cutoff month in December. Figure **??** and **??** in section A.4.3 plot the time-varying risks estimated for quarterly and annual frequency, respectively.

A.4. Wage risk estimation under alternative assumptions

A.4.1. Baseline estimation

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

$$
\begin{aligned}
& var(\Delta e_{i,t}) = var(\psi_t + \theta_t - \theta_{t-1}) = \sigma^2_{\psi,t} + \sigma^2_{\theta,t} + \sigma^2_{\theta,t-1} \\
& cov(\Delta e_{i,t}, \Delta e_{i,t+1}) = cov(\psi_t + \theta_t - \theta_{t-1}, \psi_{t+1} + \theta_{i,t+1} - \theta_{i,t}) = -\sigma^2_{\theta,t} \\
& cov(\Delta e_{i,t-1}, \Delta e_{i,t}) = cov(\psi_{t-1} + \theta_t - \theta_{t-1}, \psi_t + \theta_{i,t} - \theta_{i,t-1}) = -\sigma^2_{\theta,t-1}
\end{aligned}
\tag{A1}
$$

With four consecutive observations of wage of individual i from $t-2$ to t, hence three observations of first difference Δw, 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 consecutive observations of wage data is sufficient under a slightly looser restriction that the transitory risks stay constant over each 3-period horizon, between $t-1$ and $t+1$, call it $\bar{\sigma}_{\theta,t}$. In particular, we have the following identification.

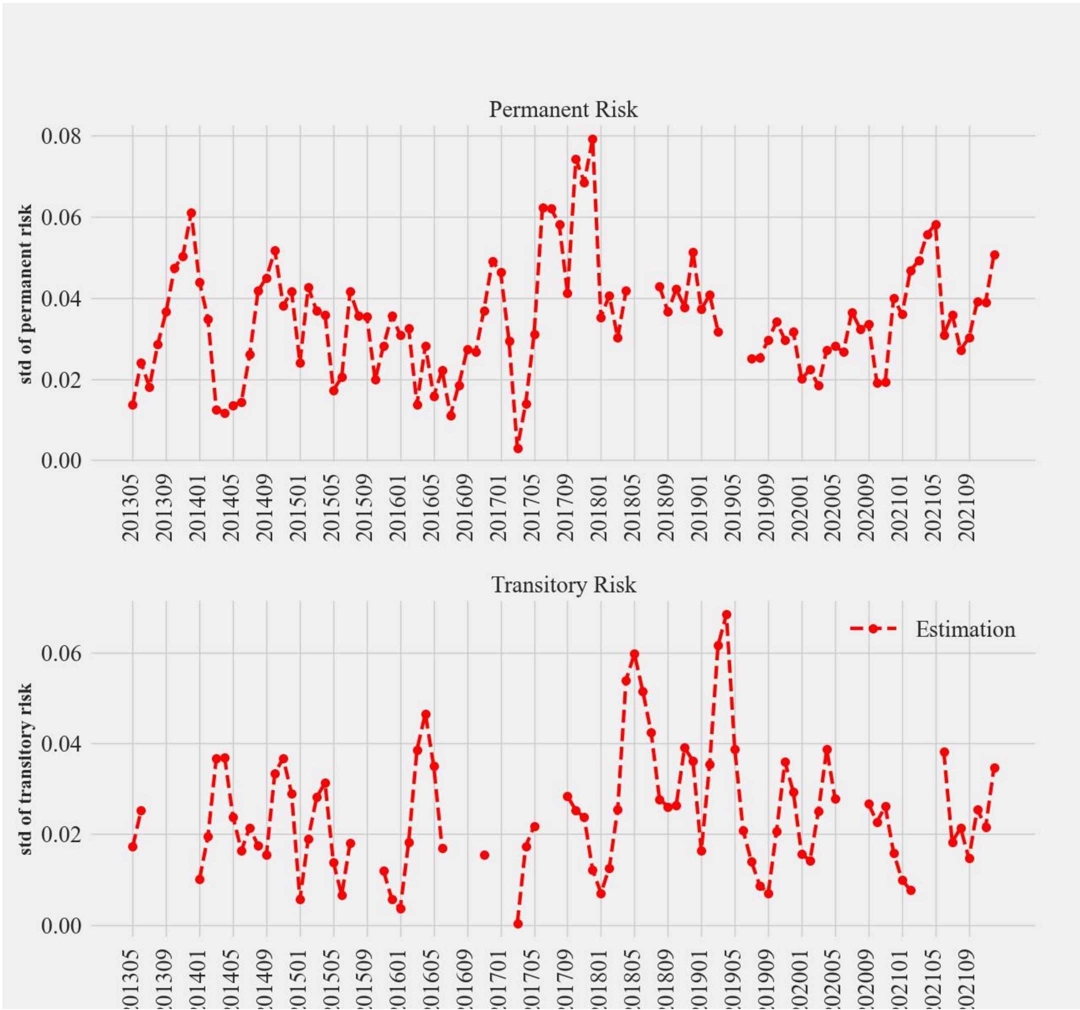
$$
\begin{aligned}
& var(\Delta w_{i,t}) = var(\psi_t + \theta_t - \theta_{t-1}) = \sigma^2_{\psi,t} + 2\bar{\sigma}^2_{\theta,t} \\
& cov(\Delta w_{i,t}, \Delta w_{i,t+1}) = cov(\Delta w_{i,t-1}, \Delta w_{i,t}) = -\bar{\sigma}^2_{\theta,t}
\end{aligned}
\tag{A2}
$$

Figure A.5 plots the identified time-varying component-specific risks under a wage process set at monthly frequency. These are used to compute the calibrated wage risks in Table 1 and Figure 1.

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, Jørgensen, and Graber (2021) shows that income dynamics at a higher frequency, i.e. monthly, require a modification to such a process to be more consistent with the data. In particular, the authors allow for infrequent arrivals of both

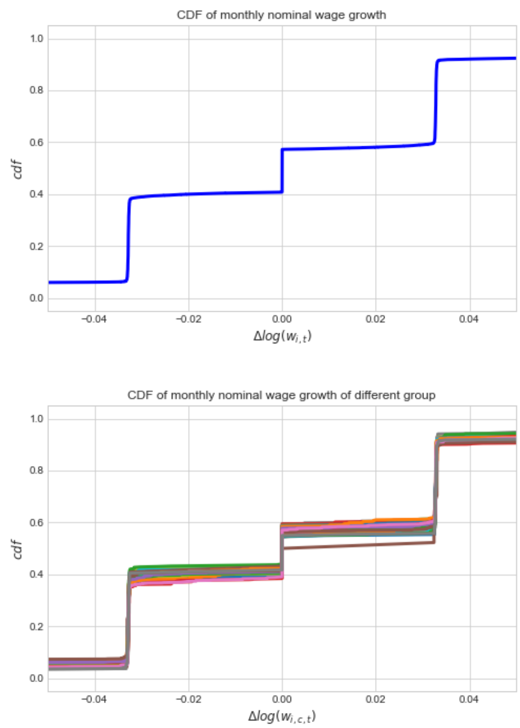
FIGURE A.5. Monthly permanent and transitory wage risks



Note: The 3-month moving average of the estimated monthly permanent and transitory risks (in std term) using the SIPP panel data on wages between 2013m1-2019m12.

transitory and permanent shocks. The assumption of infrequent shocks is primarily motivated by the observed pattern (as confirmed in Figure A.6 using nominal wage growth in SIPP) that a sizable mass of individual monthly wage growth is concentrated around zero.

FIGURE A.6. CDF of monthly wage growth



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

A.4.3. Estimated wage 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.

With wage growth in year 2014, 2015, 2016, and 2018-2021, I can identify the year-specific permanent risks for 2014, 2015, 2016, 2018, and 2019, 2020, and the average transitory risks for 2014-2016 and 2017-2019. Due to the reshuffling of the entire 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.

The estimated sample average are reported in the Table A.2. For the years with identified risks, the estimated risks at annual frequency seem to be much larger than that commonly seen in the literature, as summarized in Table A.3. In particular, the size of the permanent shock is estimated to be 32%, in contrast to the standard estimation

Table A.2. Estimated Wage Risks at Lower Frequency

YearlyPermanent	0.324408
YearlyTransitory	0.233421
QuarterlyPermanent	0.313773
QuarterlyTransitory	0.120022

Note: expressed in standard deviation units. For yearly estimates year-over-year growth of monthly wage rates are used.

of 10-15%. And the transitory risks are estimated to be around 23%, which also exceeds the standard estimates of 10% to 20%.

A similar pattern can be seen from quarterly estimates using quarterly growth of average wage rates.(See also in Table A.3)

A.5. Homogenous and heterogeneous life-cycle wage profiles

Figure A.7 plots the deterministic wage profile used to calibrate the baseline model, which is estimated from SIPP for job-stayers. Figure A.8 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.

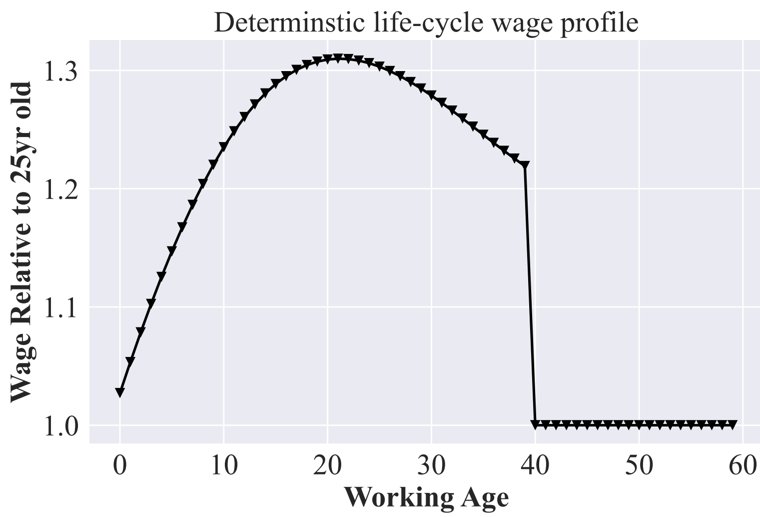
A.6. Calibration heterogeneous income risks/growth rates using the survey

In addition to fitting a truncated log-normal distribution to the heterogeneous PRs, I also calibrated the heterogeneity in perceived job finding probability, job separation probability and expected wage growth rates in the same manner. (See Figure A.9 for the illustration)

A.7. Income risks in the existing literature

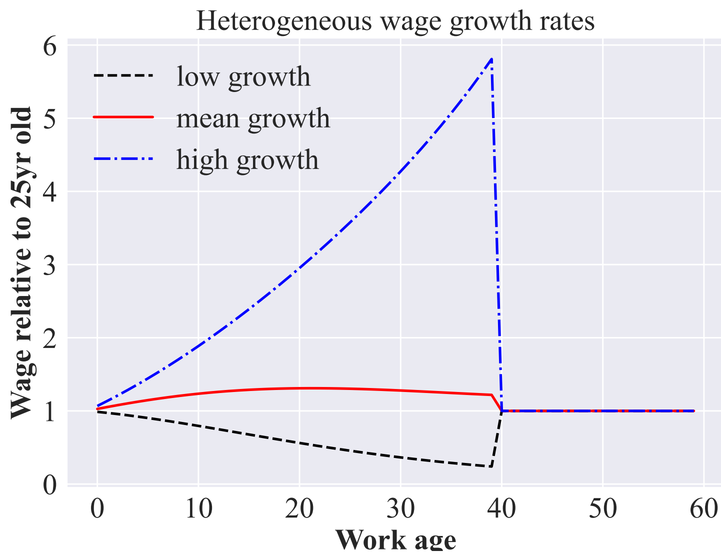
Table A.3 summarizes the most common estimates of income risks seen in the literature.

FIGURE A.7. Estimated deterministic wage profile over the life cycle



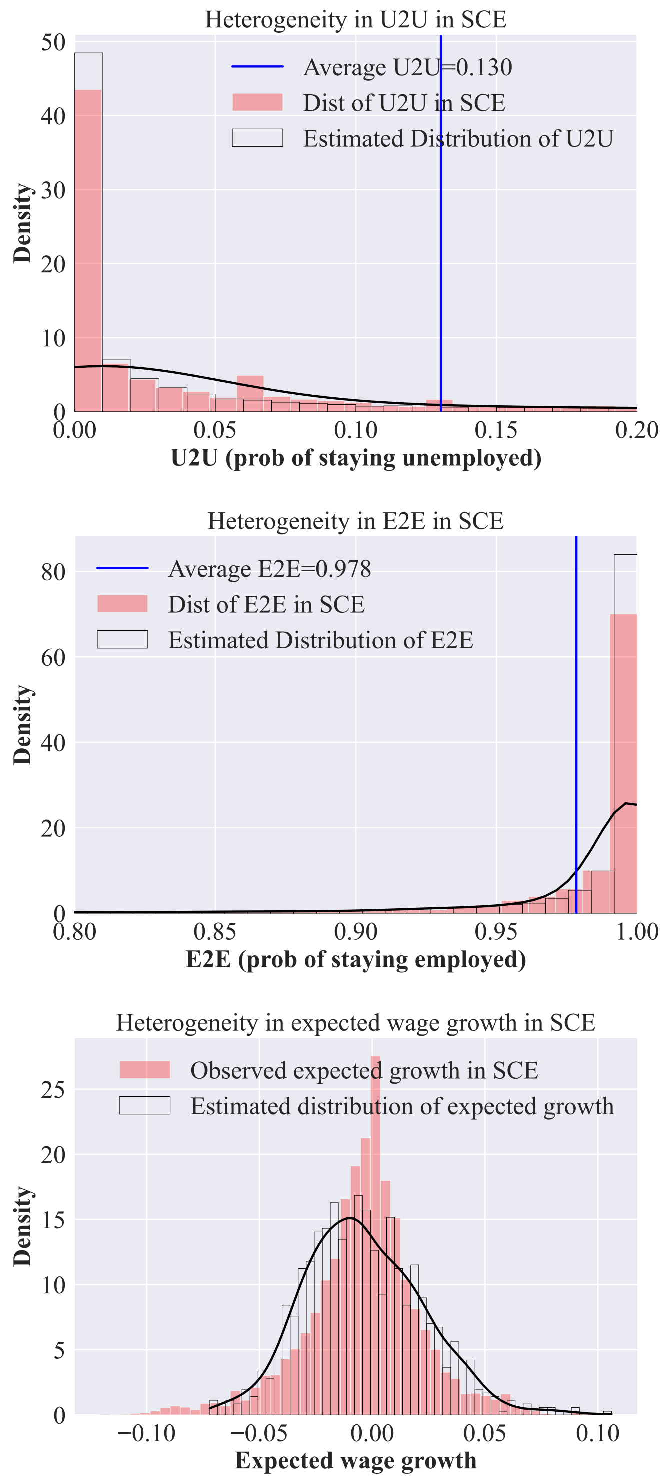
Note: this profile is used for all model calibrations. It is based on a regression of fourth-order age polynomials of real wage from the primary job in SIPP between 2013m3-2019m12 controlling for time, education, occupations, gender, etc. The post-retirement profile is assumed to stay flat after a one-time drop.

FIGURE A.8. Heterogeneous wage profiles over the life-cycle



Note: These three equally probable heterogeneous deterministic wage profiles are used to calibrate *LPR*, *HPR*, and *HPRUR* models. They are calibrated to be consistent with the estimates of σ_{ξ}^{ψ}.

FIGURE A.9. 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.3. The size and nature of idiosyncratic income risks in the literature

	σ_ψ	σ_θ	$\mho$	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, Telmer, and Yaron (2004)	[0.094; +]	0.255	N/A	N/A	Persistent + transitory	No	Table 2
Blundell, Pistaferri, and Preston (2008)	[0.1,+]	[0.169,+]	N/A	N/A	Permanent + MA	No	Table 6
Low, Meghir, and Pistaferri (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, Mitman, and Perri (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

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