Perceived versus Calibrated Income Risks in Heterogeneous-Agent Consumption Models

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December 15, 2023

[Most Recent Draft]

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

JEL Codes: D14, E21, E71, G51

Bank of Canada, taowangeconomics@gmail.com. This paper was originally circulated with the title *Perceived Income Risks*. I thank Chris Carroll, Jonathan Wright, Robert Moffitt, Yujung Hwang, Francesco Bianchi, Andrew Caplin, Edmund Crawley, Mateo Velasquez-Giraldo, Johannes Stroebel, Jonathan Parker, Corina Boar, Yueran Ma, Xincheng Qiu, Eric Huang, Jeppe Druedahl, Thomas H Jørgensen, Johannes Wohlfart, Adrian Monninger, Greg Duffee, Stelios Fourakis, Xing Guo, Zheng Liu, Matías Vieyra, the participants of the PhD conference at Yale SOM, the reading group at UPenn, the 4th Behavioral Macro Workshop, ESA Bologa, SNDE, Midwest Macro (2022), Asian Meeting of Econometric Society (2023), EEA-ES Meeting (2023) for the useful comments. Also, I am thankful for William Du's contribution to the development of computational methods in this paper.

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 savings, 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 constraints induce precautionary savings. It is widely accepted, on the basis of empirical research, that idiosyncratic income risks are at most partially insured (Blundell et al. 2008) and that such market incompleteness leads to ex-post wealth inequality[1] and different degrees of the marginal propensity to consume (MPC) (Krueger et al. 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 savings motives—another source of business cycle fluctuations.[3]

The size and heterogeneity of the income risks are two 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] However, this estimation practice has limitations.

The method economists use 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 assumption is simple: Certain information, each individual's intrinsic heterogeneity or advance information about future income or risks, that enters an agent's information set from time to time is not directly observable by economists. If the risks economists calibrate based on flawed estimations differ from those the agents perceive then the model's implications will fail to match the agents' behavior even if the model is right (except for the case of a miscalibration).

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 Expectations* (SCE).

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

[2] Krueger et al. (2016),Kaplan et al. (2018), Auclert (2019).

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

[4] Some recent examples include Krueger et al. (2016), Bayer et al. (2019), Kaplan et al. (2018).

Compared to the previous work that studied partial insurance using 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; they also report their perceived job-finding and separation probabilities and answer 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 risk perception that presumably guides individual decisions.

With the individual-specific reported perceived risks (PR) in hand, I first confirm that the differences in the mean risks 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 risks than middle-aged middle-income males). However, patterns do not often align between the two; that is, perceived risks, unlike calibrated risks, decrease with education level. More importantly, within every such group, there is also a great deal of heterogeneity in the PR that is not captured using the conventional approach. The R^2 from regressing the PR on the conventional explanatory variables is only about 0.1, indicating that the traditional method fails to capture 90 percent of the heterogeneity in the perceived risks.

In addition, the paper also finds that the perceived income risks, on average, are *lower* than the indirectly calibrated size of the 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 et al. (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 external estimates of the risks, based on various income measures in the existing literature (Table A.3). This finding is corroborated by a closely related contemporaneous study by Caplin et al. (2023), who also show that survey-reported earnings risks are lower than their indirectly estimated counterparts that use Danish administrative records.

This evidence motivates me to utilize survey-implied risks, as agents truly perceive

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

that the data calibrate income risks in a standard incomplete-market overlapping-generation general-equilibrium model to quantify these effects. The baseline model blends the work of Huggett (1996), the income structure of Carroll and Samwick (1997), and the persistent unemployment spells and unemployment benefits a la Krueger et al. (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 the 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 risks than in the baseline model implies less motivation for precautionary savings, 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 translates to heterogeneous savings 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; that is, one- and two-thirds, respectively, of the 13 percentage point increase of the wealth Gini. Meanwhile, the heterogeneity in the unemployment risk is the key to accounting for a larger share of H2M households being closer to the data; that is, an increase of 13 percentage points out of 17 in the share of H2M households is attributed to the realistic calibration of the 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 purposes within a single model. First, it serves as a robustness check with an alternative model assumption deviating from the FIRE. Although our benchmark assumes that

[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 that deviate from the FIRE. See, for example, Mankiw et al. (2003), Reis (2006), Coibion and Gorodnichenko (2012), and Wang (2022). However, most of this type of evidence is based on macroeconomic expectations, such as that of inflation.

when agents' perceived risks are lower than the indirectly calibrated risks, due to the existence of unobserved heterogeneity, it is also possible that agents simply under perceive the true degree of the 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 savings behavior resulting from risk perceptions, or the "choice" channel, and the other via ex-post realized income inequality, or the "outcome" channel.

The main finding from this extension is that the "choice" channel is the key: Even if the objective risks remain the same as the conventional calibration, letting consumption/savings decisions be driven by the survey-reported risks alone is sufficient to yield a closer match of the model with the empirically measured wealth inequality and the fraction of low-liquid-asset-holding consumers. This reinforces a message that is echoed by many other studies that are based on expectation surveys: directly reported perceptions, albeit possibly subjective, still better explain the behaviors of heterogeneous agents and generate more-realistic downstream macroeconomic implications than indirectly calibrated expectations that 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 the research methodology between the two is how we compare the subjective risks with their conventional counterparts. Caplin et al. (2023) first simulate unconditional distributions of earnings based on the surveyed beliefs and compare these with Danish cross-sectional administrative records. In contrast, this paper estimates the conditional risks using a panel data structure following the common practice in the income risk/HA-macro literature and compares this with the conditional perceptions reported in the survey. Despite such differences in methodology and datasets, both studies find the perceived earnings risks to be lower than those indirectly inferred from their conventional counterparts, which are primarily attributed to unobserved heterogeneity. Furthermore, the two studies explore the macroeconomic implications of the 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 et al. (2016); and Carroll et al. (2017), with a primary focus on liquid wealth accumulation, while Caplin et al. (2023) work with a search and matching model.

In addition, 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 the consumption insurance. Early work by MaCurdy (1982), Abowd and Card (1989), Gottschalk et al. (1994), and Carroll and Samwick (1997) initiated what is now a common practice, in the literature, of estimating income risks by decomposing them into components of varying persistence on the basis of the panel data. Subsequent work 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 et al. (2008) used the same specification of the 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 highlights the asymmetry and cyclical behaviors of idiosyncratic earnings/income risks (Storesletten et al. 2004; Guvenen et al. 2014; Arellano et al. 2017; Guvenen et al. 2019; Bayer et al. 2019; Guvenen et al. 2021). Additionally, a separate literature has focused on job-separation and unemployment risks (Stephens Jr 2004; Low et al. 2010; Davis and Von Wachter 2011; Jäger et al. 2022). Table A.3, in the Appendix, summarizes the income process and estimated risks discussed in selected papers from this literature. Compared to this work, the novelty of this paper lies in its focus on 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 the consumption response to income shocks, there is always a concern that what is interpreted as a shock has actually already entered the agents' information set. If so, this may lead to the finding of the "excess smoothness" of supposedly unanticipated shocks (Flavin 1988). My paper is in the spirit of these studies in that we all use surveyed expectations to tackle the identification problem.[10] That is, I directly use expectations 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' in-

[8] Synthesizing various data sources, Moffitt (2020) found no such obvious trend for the same period.

[9] Koşar and Van der Klaauw (2022) provide a recent exception, as they document the cross-sectional/life-cycle/business heterogeneity in perceived earnings risks, using SCE data.

[10] See Karahan et al. (2017) for a similar exercise.

formation 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 estimated risks using the difference between the expectations and the realizations. An advantage of my approach is that I can directly study individual-specific risks instead of those at the group level.

Third, the paper speaks to an old but recently revived trend in the literature of studying consumption/savings behaviors in models that incorporate imperfect expectations and perceptions. For instance, Pischke (1995) explored the implications of 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 savings motives. Guvenen (2007) emphasized the role of heterogeneity in life-cycle income profiles and models' agents learning about the trend component through sequential income realizations. To reconcile the low MPCs in the microdata and the high MPCs in the macro level, Carroll et al. (2018) introduced the information rigidity of households that are learning about the macro news while they are fully updated on the micro news. Rozsypal and Schlafmann (2023) found that households' expectations about incomes exhibit over-persistent bias. More recently, Broer et al. (2021) incorporated information choice in a standard consumption/savings model to explore its implications for wealth inequality. My paper has a similar flavor to all of 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 the income risks. Second, although most of the existing work explicitly specifies a mechanism of expectations formation that deviates from the full-information rational-expectations 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 expectations 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 et al. 2011; Manski 2018), where Dominitz and Manski (1997), particularly, explore patterns of income expectations that are 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

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

shown that respondents have a consistent ability and willingness to assign probabilities (or "percent chances") to future events. Armantier et al. (2017) thoroughly discuss designing, experimenting, and implementing consumer expectations surveys to ensure the quality of the responses. Broadly speaking, advocates have argued, first, that analysts must go beyond the "revealed preferences" 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 not only for point forecasts but also for risk/uncertainty; this is because for any economic decision made by a risk-averse agent, both the expectations and the perceived risks matter a great deal.

Finally, this paper is related empirically to the literature that studies expectations formation using subjective surveys. In recent decades, a long list of theories of "expectations formation" alternatives to the FIRE have been developed, each of which examines how agents deviate from full-information rationality benchmarks, such as sticky expectations, noisy signal extraction, and least-square learning, among others. 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, the 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 risk

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

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

There is an extensive discussion in the literature about the exact time-series nature of the stochastic component e. For instance, it may consist of both of a permanent and a transitory component.[12] Or some of the literature may replace the permanent component with a stationary/persistent component in the form of an autoregressive (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.

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

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

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

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

The predictable changes do not enter the 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 this crucially depends on the time-series nature of $e_{i,t}$.

Economists do not directly observe the size of the true PR. 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 the observed wage growth in the panel data, $\Delta w_{i,t}$, by the approximated 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 the age polynomials,

[12] Abowd and Card (1989), Gottschalk et al. (1994), Carroll and Samwick (1997), Blundell et al. (2008), and Kaplan and Violante (2010).
[13] Storesletten et al. (2004), Guvenen (2007), Guvenen (2009).
[14] Meghir and Pistaferri (2004).

gender, education, and occupation. 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 the income risk. It is usually referred to in the literature as the "volatility." [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 common practice usually estimates income risks at the group level, denoted as c (such as age, education, and cohort), although, in theory, the risks as perceived by an FIRE agent could be totally individual specific. This is because, at the individual level, there are no realizations of the risks but a particular realization of the shock is drawn (Equation 4). The within-group cross-sectional variation of a sufficiently large group size is needed for such an estimation.

Unlike the agent's PR, $Var_c(\Delta\hat{e}_{i,c,t})$ is an *unconditional* variance at the group level. It is crucial to make a distinction between the agent's *conditional* PR and the *unconditional* volatility that economists approximate. Two important issues affect the comparability of the two.

First, it is very likely that what is controlled for in the first step of the 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] This is primarily because econometricians who have the earnings panel data cannot control for the "unobserved heterogeneity" that is 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, information that is not available to econometricians. For instance, a worker might be concerned that a recent dispute with their boss may negatively affect their wage the 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 the economists' estimated volatility is unconditional, while the perception is conditional on the information until time t. To illustrate this point, imagine a very persistent component in the income shock. Under the aforementioned process, the estimated income volatility also includes the variance of the realized shock until t,

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

[16] In later sections of the paper, I relax the FIRE assumption, which makes it possible that the PR reported in the survey is also subject to the agents' incomplete information and behavioral bias at time t.

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

which has already entered the agent's information set. Therefore, even if the econometricians perfectly recover the $e_{i,t}$ in the first-step regression, the presence of a persistent component in the income changes would result in differences between the PR and the estimated income volatility. Therefore, to approximate the true PR from the point of view of the agents, economists would 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, the survey-elicited PR has an invaluable use and is preferable to a 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 each agent's information set, i, which is likely to include the intrinsic heterogeneity specific to the individual or the advance information useful for 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, the survey-implied PR provides direct identification of the degree of heterogeneity of the income risk across individuals in the economy. This prevents modellers from possibly making 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 who are subject to certain behavioral biases, such as overconfidence, in contrast to those biases that are assumed by the FIRE. In the next section, I explore the robustness of the paper's model results with respect to these alternative assumptions. The key takeaway is that even if the survey-implied PRs do not align with the true objective size of the income risks, they prove to be a better input for predicting individual decisions than the calibrated income risks 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 Expectations* (SCE), conducted by the New York Fed, a monthly online survey for a rotating panel data of around 1,300 household heads during the period June 2013 to July 2021, or over 97 months.

I primarily rely upon the density forecast of individual earnings by each respondent in the survey to estimate the perceived income risks. The main question used is framed as follows: "Suppose that 12 months from now, you are working in the exact same job at the exact same place for 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 taxes and other 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 provided in the 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 the adjusted PR in real terms and the nominal PR for the empirical results below.

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

First, focusing on the wage risk avoids the problem of misconstruing changes in the earnings due the risks associated with voluntary labor supply decisions. 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 the uninsured idiosyncratic risks. The survey-based measure used here is not subject to this problem. Second, the wage risk also excludes important sources of income fluctuations, such as unemployment and job switching. As research demonstrates

[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 et al. (2009) and researchers in the New York Fed (Armantier et al. 2017). Appendix A.1 documents in detail the estimation methodology and its robustness.

(Low et al. 2010), major job transitions are often the dominant source of the income risks individual workers face. In Section 4.4, I separately examine unemployment risk expectations, surveyed as perceived job-separation and finding probabilities in the SCE.[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 the SIPP, which surveys approximately 1,000 to 2,000 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 the SIPP to estimate the wage risk has obvious advantages over other commonly used datasets, the most notable of which is the *Panel Study of Income Dynamics* (PSID). The SIPP contains information that allows me to work with wage changes conditional on staying in the same job with the same employer, thanks to its detailed records of job transitions and unique employer identifier. In contrast, the PSID only provides biennial records of labor earnings for the years since 1997. For the overlapping periods between the SIPP and the SCE, it is possible to make a direct comparison between the realized wage risks at annual frequencies and the ex-ante perceptions of the wage risk. This is particularly crucial if the wage risk is time-varying and dependent on macroeconomic conditions.

To ensure the comparability between the perceptions and the 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 number of hours of work for the same job for only those who stay with the same employer for at least 2 years. To identify

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

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

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

job stayers, I follow the same approach as Low et al. (2010) and I impose five criteria. I only include (1) the working-age population between age 25 and 65; (2) private-sector jobs, excluding workers employed in government or other public sectors; (3) those remaining in the same job as the previous year; (4) those whose monthly wage rates are no greater than 10 times or smaller than 0.1 times of the average wage; and (5) those who do not have days away from work without pay during the reference month. This leaves me with a monthly panel of from 350 to 1,000 individual earners for the sample period, 2013m3-2019m12. Appendix A.3 discusses in greater detail the data selection procedure and reports the summary statistics.

4. Basic facts about perceived income risks

4.1. Observable and unobservable heterogeneity in the perceived risk

In both income risk estimation and the parameterization of 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, that 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 the PR across individuals does reflect between-group differences along dimensions economists have commonly assumed, a dominant fraction of the differences in the PR can be attributed to other unobservable heterogeneities. Furthermore, even in those observable dimensions, the group heterogeneity seen in the PR does not coincide with that seen in the estimated risks.

Figure 1 plots the group average of the PRs (both in real and nominal terms), the 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 an estimation of a specified wage process (see the next section for the exact procedure used to generate this) by age, gender, and education. Regarding the education profile of the wage risk, both the wage volatility and the calibrated risks are higher for more-educated workers. This is consistent with the finding of Meghir and Pistaferri (2004), who examined total labor income instead of the wage. In contrast, risk perceptions exhibit the opposite pattern with respect to education

[24] For instance, Meghir and Pistaferri (2004) found that more-educated workers face higher income risks than less-educated workers. 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 et al. (2008), and Carroll et al. (2017) allowed for heterogeneous risks across different demographic variables.

level: less-educated workers report higher PRs than more-educated workers. Regarding the life-cycle pattern of risks, neither the wage volatility nor the estimated risks show a monotone pattern over the life 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 PR, the wage volatility and the estimated risks.

The second salient fact is that the PR is always *smaller* than the wage volatility and, most of the time, it is also smaller than the calibrated wage risk. In particular, the volatility of year-over-year wage growth is well above 30% and the calibrated risk of different groups fall in the range of 5-15% per year (in standard deviation terms). 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 than the calibrated risks. 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%.

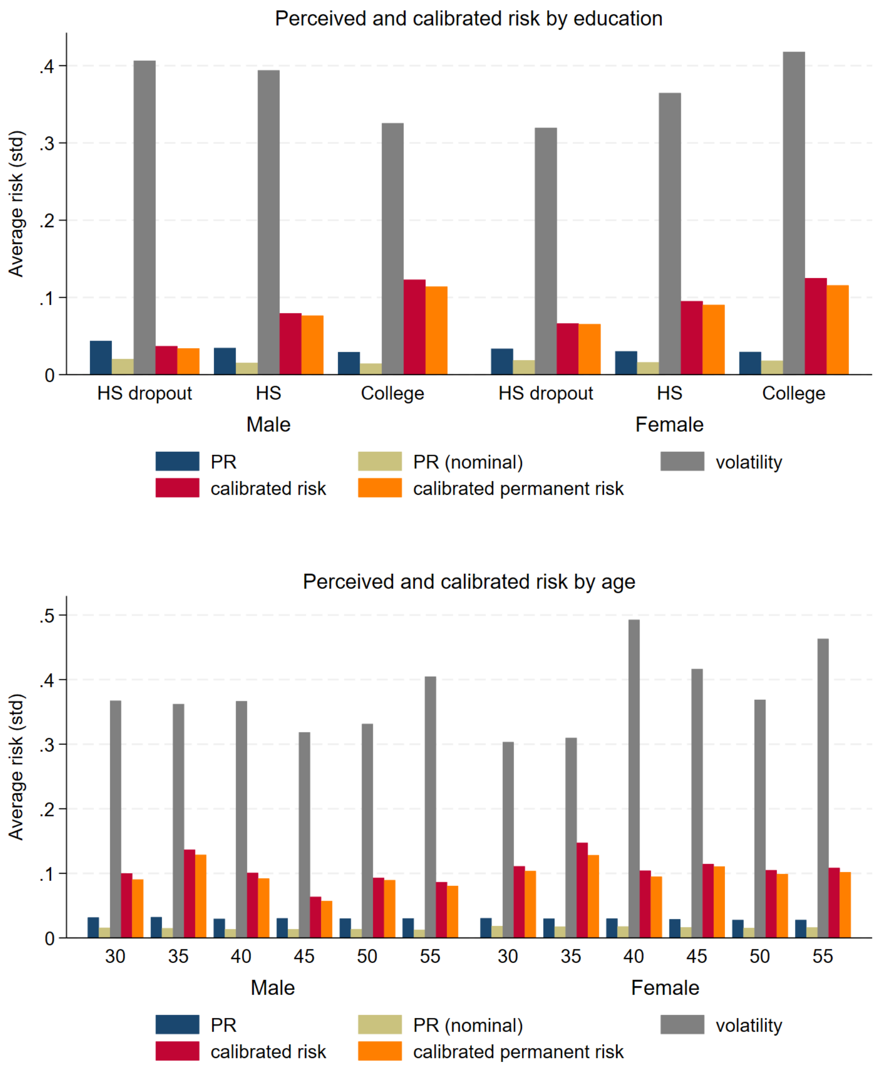
Such a size difference is also evident in the Figure 2, which plots the distribution of the PRs against the distribution of the individual-level annual wage volatility in the SIPP that can be explained by observable demographic variables such as age, gender, and education. This corresponds to our wage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

Another finding in addition to the size difference is that the PRs are more heterogeneous than those of the wage volatility that can be explained by the observable factors. This can be confirmed by observing in Figure 2 that the dispersion of the PRs is significantly larger than the explainable dispersion of the individual volatilities. Consistent with this, the R^2 of a regression of the PR on all of the observable factors in the SCE,

[25]The homogeneous age pattern of the wage risk is not necessarily contradictory with the well-documented declining pattern estimated using data on household income or total earnings[26]. It is likely that the decline in 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 those by Low et al. (2010), as their study explicitly estimates the wage risk of job stayers separately from job-switching and unemployment spells. The authors report that annual permanent and transitory risks are each 10%. This implies a total risk of approximately 35%-40%.

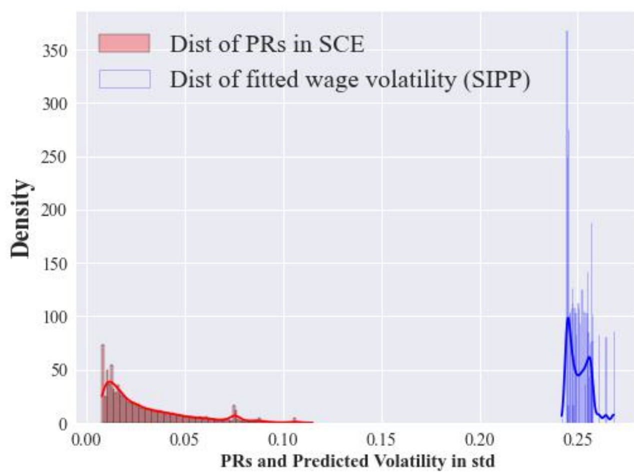
FIGURE 1. Perceived risks, wage volatility, and calibrated wage risks by observable factors



Note: Real and nominal perceived risk (from the SCE), average estimated wage volatility (from the SIPP), estimated/calibrated wage risk and permanent risk (from the 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 the log changes in the unexplained wage residuals, as defined in Equation 4. The calibrated risk is equal to the estimated risk of the permanent and transitory component of the wage, based on the process specified in Equation 5.

without the individual fixed effects, is at most 10%, while including the fixed effects increases the R^2 to 70%.[28] This finding has two implications. First, the role of the within-group heterogeneity suggests that the conventional practice of estimating and modeling the income risks as only differing by demographic dimensions has limitations. Second, the heterogeneity in the PR can be directly put into use to model the heterogeneous income risks without identifying the source of the heterogeneity. Therefore, in Section 5, my model calibration adopts such an approach.

FIGURE 2. Dispersion in the perceived wage risk



Note: Distributions of the PRs regarding the real wage growth in the SCF and the individual wage volatility are explained by the 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 the future wage, while an entirely transitory shock does not. Therefore, in the two scenarios, the agents perceive different degrees of risk. This is crucial to making

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

a fair comparison between the survey-reported PRs and the calibrated risks using conventional methods.

To proceed, I adopt an income/wage process commonly used 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 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 the panel data, provided that the change in the 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 $\sigma^2_{\theta,t-1}$ precisely due to its unconditional nature. The intuition here is that the variance of the transitory shock that is realized at time $t-1$ is no longer perceived as the wage growth risk conditional at time t.

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

[29] MaCurdy (1982), Abowd and Card (1989), Gottschalk et al. (1994), Carroll and Samwick (1997), Blundell et al. (2008), among others. Crawley et al. (2022) present a more parsimonious process to resolve the possible model misspecification caused by the “time-aggregation” problem.

[30] This also corresponds to the model specification 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 et al. (2008), which consist of minor differences depending on the model specification.

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

Table 1 reports the group-specific estimates of the total, permanent, and transitory wage risks based on the 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 the indirectly estimated risks (Calibrated Risks), even if the latter are 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 the PRs and the calibrated risks remain.

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

The most likely explanation for this disconnect in both the size and the time-varying patterns between the two series is either the unobservable heterogeneity or the superior information, one point I will formally elaborate in the next section. For the common panel-data-based estimation to correctly identify the idiosyncratic wage risks relevant to heterogeneous individuals, two requirements need to be satisfied. First, economists need to perfectly exclude the predictable changes in the wage growth from the point of the agent by both correctly approximating $z_{i,t}$ in the first-step regression and by correctly decomposing the various components' variances contained in $e_{i,t}$. Second, they also need to correctly assume the dimensions by which the risks differ across individuals. Given the stringency of these requirements, the directly reported PRs may provide a better alternative to calibrating the 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 the survey-based PRs and the calibrated risks, using panel data: the role of the unobserved heterogeneity. In the model in Section 6, I explore alternative hypotheses, such as agents' misperceptions of risks, due to behavioral biases.

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

To capture the unobserved heterogeneity (or to advance the information) explicitly, I allow for the change in the unexplained wage residual $\Delta\hat{e}_{i,t}$ based only on a small set of observables to be different from what is truly unpredictable from 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's job the next year. An example of $\Delta\xi^{\theta}_{i,t}$, an expected transitory change that is yet unlikely unobservable by researchers, is the future income cut to a professor who is 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

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

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 $\xi^{\psi}_{i,t}$, whether observable or not by economists, have exactly the same statistical properties. The same can be said for the transitory components.

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

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 the average PR in the SCE and 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 represent the size of the unobserved heterogeneity in the permanent and transitory wage changes, respectively.

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

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

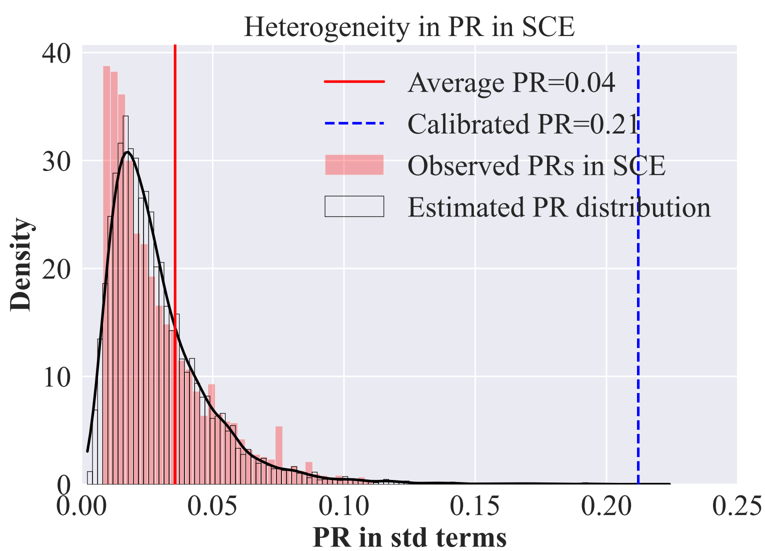
The two parameters can be straightforwardly estimated by fitting a truncated log-normal distribution to the cross-sectional distribution of the time-average PRs in the SCE, as shown in Figure 3.

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 heterogeneities: $\sigma_{\xi,\psi} = 0.13$ and

[34] Essentially, the estimated transitory risk which 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 $\hat{\sigma}^2_{\psi} = var(\Delta\hat{e}_{i,t}) - 2\hat{\sigma}^2_{\theta} = var(\Delta e_{i,t}) + (\sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta}) - 2\hat{\sigma}^2_{\theta} = \int var(\Delta e_{i,t}) di + (\sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta}) - 2\hat{\sigma}^2_{\theta} = \int (\sigma^2_{i,\psi} + 2\sigma^2_{i,\theta}) di + (\sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta}) - 2\hat{\sigma}^2_{\theta} = \int (\sigma^2_{i,\psi} + 2\sigma^2_{i,\theta}) di + \sigma^2_{\xi,\psi} + 2\sigma^2_{\xi,\theta} - 2(\int \sigma^2_{i,\theta} + \sigma^2_{\xi,\theta}) = \int \sigma^2_{i,\psi} + \sigma^2_{\xi,\psi}$.

$\sigma_{\xi,\theta} = 0.13$, and a fitted truncated-log-normal distribution of the 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 of Low et al. (2010), $\sigma_{\psi} = 0.10$ and $\sigma_{\psi} = 0.09$ yield smaller estimates of the unobserved heterogeneities $\sigma_{\xi,\psi} = 0.08$, $\sigma_{\xi,\theta} = 0.07$. In both cases, the estimates imply that a dominant fraction of the observed wage inequality and volatility is attributed to unobserved heterogeneity, instead of the risks, according to the conventional calibration of the model. This is based on the assumption that the PRs truly reflect the degree of risk the agents face.

FIGURE 3. Estimated heterogeneity in the perceived risks



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

4.4. Unemployment risk perceptions

My analysis has so far focused only on the wage risk conditional on staying in the same job. But this only constitutes part of the income risk, 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

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

incomplete-market macroeconomic models.[36] In these models, as in the approach to the wage risk, 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 and finding probabilities track the realized aggregate dynamics computed through panel data following a standard approach in the search & matching labor literature, as in Fujita and Ramey (2009), survey-reported expectations mask a huge amount of heterogeneity, which is not assumed in standard models.

To achieve a fair comparison between the 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 the job-separation and finding rates, respectively, against the corresponding average, and the 25/75 percentile of the expectations across all of the 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, the perceptions track the aggregate realizations relatively well. The most notable deviation between the beliefs and the realizations occurred during March 2020, which saw an unprecedented increase in one-month job separations[39] and a dramatic decrease in job finding. Second, however, as shown by the wide 25/75 inter-range percentile around the mean expectations, individual respondents vastly disagree on their individual separation and finding probabilities. Because the question in the survey concerns individual-specific transitions, it is reasonable to assume that this reflects either the unobserved heterogeneity or the information available on each individual's status, which economists cannot directly observe.

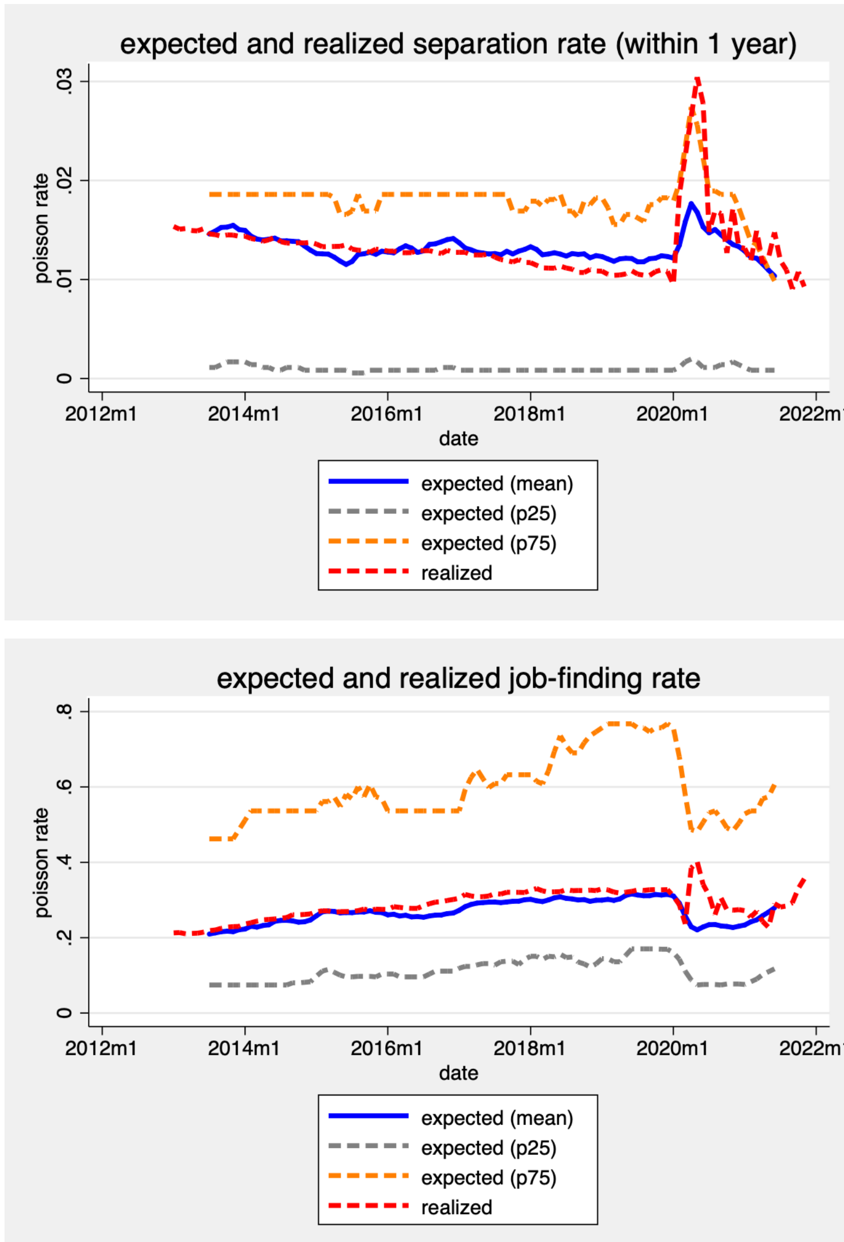
[36]For examples, see Krueger et al. (2016) and Bayer et al. (2019), among others.

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

[38]Assuming the reported probability of separation from the current job in the next 12 months is $P_{i,t}(ue_{t+12}|e_t)$, 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 the *Current Population Survey* (CPS) $P(ue_{t+1}|e_t)$, the corresponding realized Poisson rate is $-log(1-P(ue_{t+1}|e_t))$.

[39]The observations for March 2020 were dropped in the graph; otherwise, they would have overshadowed all of the other observations in the sample.

FIGURE 4. Expected and realized job-separation and finding rates



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

4.5. Perceived income risk and consumption spending

Due to precautionary savings motives, higher perceived risks induce households to lower their current consumption, thus, increasing their expected consumption growth. Despite such a clear directional prediction in theory, identifying the exact size of such an effect (i.e., the perceived risks on ex-ante consumption/savings decisions that are separate from the ex-post income impacts) has been challenging when conventional data sources are used, as this does not directly elicit ex-ante plans and perceptions at the individual level. This section shows that the coexistence of the same individual's individual-specific perceived risks and consumption plan, as documented in the SCE, provides a rare opportunity to resolve this problem.[40] This contrasts with the best practice to date, which is to impute ex-ante unemployment risks to a particular individual on the basis of only a number of observable factors from the realizations (Harmenberg and Öberg 2021).

I run a regression of the expected consumption growth reported in the SCE by each respondent on the same individual's expected wage growth and 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 operates on the assumption that such a reduced-form regression clearly corresponds to the commonly used approximated Euler Equation to the second order (Parker and Preston 2005), where the expected consumption growth is equal to the sum of the intertemporal substitution and the precautionary savings motive. However, a linearly approximated Euler equation is reasonable only under a set of unrealistic and stringent assumptions, such as the absence of an external borrowing constraint, the absence of buffer-stock-savings 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 qualitative effects of precautionary

[40] Guiso et al. (1992) provide an early example of directly testing precautionary savings motives using the reported subjective income risks of Italian households. Other recent works that examine the impacts of expectations on readiness to spend include Bachmann et al. (2015) and Coibion et al. (2020). Recently, in closely related studies, Fuster et al. (2020) and Bunn et al. (2018) relied on survey answers to measure the stated marginal propensity to consume. Most related to this paper, Christelis et al. (2020) also found that expected consumption growth is positively correlated with perceived income risk at the individual level, based on Dutch households.

savings motives, without providing a structural interpretation of the size of the estimated coefficient.

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

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.

[41] One common econometric concern with running regressions of this kind is the measurement error in the regressor; that is, 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 the expected spending growth is indeed positively correlated with the perceived risks, taking into account the bias, then this implies that the correlation between the two is greater.

5. Perceived risks and wealth inequality

Section 4.5 provides assuring evidence that individual consumption/savings 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 using 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 à la Carroll and Samwick (1997), Krueger et al. (2016) and Carroll et al. (2017).

In each period, a continuum of agents is born. Each agent i lives for L and has worked for T ($T \leq L$) periods since entering the labor market, during which they earn stochastic labor income y_τ at the working age of τ. After retiring at the age of T, the agent lives for another $L-T$ periods of life and receives social security benefits. Without aggregate risks, there is no need to treat the calendar time t and the working age τ as two separate state variables; hence, I suppress the 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 their expected life-long utility under a discount factor β and their potentially age-dependent survival probabilities $1-D$.

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

where $c_{i,\tau}$ represents consumption at working age 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 the total cash in hand at the beginning of the period τ as $m_{i,\tau}$, the end-of-period savings 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 a rate of λ and the social security tax rate is λ_{SS}. R is the gross real interest rate 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 savings 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 between $\tau = 1$ to $\tau = T$ while they are of working age and receives a social security benefit after retirement. The income processes in both subperiods 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 component $\xi_{i,\tau}$. The aggregate wage is to be determined by the forces of general equilibrium.

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

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

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

During the working life, 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 $\{G_\tau\}_{\tau=1\ldots L}$.

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

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

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

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 $\tau = T$. The agent receives social security with a replacement ratio, $\mathbb{S}$, proportional to their permanent wage and the 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.

The parameters governing the degree of the income risk while the individual is of working age ($\tau \leq T$), in this model, consist of the standard deviations of the permanent and transitory wage shocks σ^2_ψ and σ^2_θ, respectively, as well as the transition probabilities of the job spells. For both types of wage shocks, we assume standard normal distributions.[44]

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

(14)
$$\psi_{i,\tau} \sim N(-\frac{\sigma_\psi^2}{2}, \sigma_\psi^2)$$
$$\theta_{i,\tau} \sim N(-\frac{\sigma_\theta^2}{2}, \sigma_\theta^2)$$

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

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

In general, this assumption implies to some degree that unemployment risks persist, but this assumption 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 employment status.

Unemployment risks are idiosyncratic. Hence, by the law of large numbers, the fraction of the population that is either unemployed or employed at each age, denoted by $\Pi_\tau^{\mho}$ and Π_τ^{E}, respectively, is essentially deterministic and not dependent on age.

It is worth pointing out that I assume that all of the parameters of the income risks σ_ψ, σ_θ, $\mho$, and E are age invariant. This allows me to avoid restricting the heterogeneity in the income risks only to 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 of the earlier periods ($\tau < L$), respectively.

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

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

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

where the three state variables for the agents are the current employment status $\nu_{i,\tau}$, the total cash in hand $m_{i,\tau}$, and the 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 savings policies, $a^*_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau})$. Both are functions of all of the state variables.

5.1.4. Technology

The economy has a standard constant-return-to-scale technology that turns capital and the supplied efficient units of labor into aggregate output.

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

Capital depreciates at a rate of δ each period. The factors of the 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 survival at each age and the latter is a normalization that guarantees that the fractions of all age groups sum up to 1.[47]

5.1.6. Government

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

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

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 those of 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 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 agents of all ages τ. The distribution of agents by age $\tau=1$ depends on the initial condition of the labor income outcomes and the size of the 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's 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 of the 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 savings policies $c(x,\tau)$, $a(x,\tau)$ as

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

[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 iterations of multiplying the distribution of agents at age $\tau-1$ by the transition matrix of to age τ.

well as constant production factor prices, including the real interest rate R and the wage W, the initial wealth of newborns b_1, the unemployment benefit ζ, the tax rate λ, and the time-invariant distribution $(\psi_1, \psi_2, \ldots, \psi_L)$ such that

1. consumption and savings policies are optimal, given the real interest rate R, the 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 household behaviors, as described in Equation 21.

3. the factor markets are clearing:

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

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 balances of newborns are equal to their accidental bequests:

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

and

6. the government budget is balanced as described in Equations 19 and 20.

The economy may potentially arrive at different stationary equilibria, 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 the 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 yearly frequencies. The working age spans from 25 to 65 years old ($T = 40$) and the agent dies with certainty at age 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 the SIPP for workers aged 25-65, while controlling for other observable demographic variables such as education, gender, occupation, and time fixed effects.[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 the permanent wage at age 66; that is, $G_{41} = 0.8$, and that the permanent wage stays flat till death. This produces an average expected growth factor of the permanent wage being exactly equal to one over the entire working life. 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 the consumption/savings 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 0.6 in order to match the heterogeneity in the "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 the SIPP (as reported in Table 1), I thoroughly 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 of the risks into the annual frequencies (because some of the estimates are for different frequencies). Whenever group-specific risks are assumed (depending on education and age), I summarize them as a range. Also, for models that assume a persistent

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

instead of a permanent component, I treat the assumed size of the persistent risks as a lower bound for the permanent risks.[51] For models with income risks dependent on aggregate business cycles, a la Krusell and Smith (1998), I compute the steady-state size of the idiosyncratic risks by 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 presumably for the risk that is the most comparable to the surveyed PRs among them, the wage risk estimate by Low et al. (2010). I use the median values of each parameter in the literature as the benchmark income risks profile, which is a combination of $\sigma_\psi = 0.15$ and $\sigma_\theta = 0.15$. Following the calibration of Krueger et al. (2016), the yearly probability of staying unemployed 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 of $K/Y = 3$ at the steady-state level of employment in the model.

Government policies. As in Krueger et al. (2016), the unemployment insurance replacement ratio is set to be $\mu = 0.15$. The pension income relative to 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 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 the two preference parameters using consensus values instead of internally calibrating them to match the moments such as the mean or median wealth/income ratios in the SCF.[52]

[51] One can think of the permanent income shock as a limiting case of the AR(1) shock, with the persistence parameter infinitely close to 1. The effective income risks increase with the persistence of the shock.

[52] Kaplan and Violante (2022) discuss in detail how internally calibrated discount factors in one-asset models differ depending on whether they are 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

Table 3 summarizes the parameters used in the calibration of the baseline model. This is nearly identical to what would be considered 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

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 parameterizations on permanent and transitory wage risks at annual frequencies of

ratio of 4.6. This is the same as the average value estimated in models with heterogeneous time preferences, as in Carroll et al. (2017) and Krueger et al. (2016).

σ_ψ = 0.15 and σ_θ = 0.15, and unemployment risks of $U2U$ = 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 et al. (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 the data is that the former significantly underpredicts the share of agents that are close to their 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) of less than 1%, which is significantly lower than 0.31, the share computed based on the net liquid wealth in the SCF. It is known that the strong precautionary savings motives in this model incentivize agents to build savings 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 the SCF (Figure 5). In particular, allowing the voluntary bequest in the last period of life helps me to match the savings behaviors after retirement better.

6.2. Model results with perceived risks

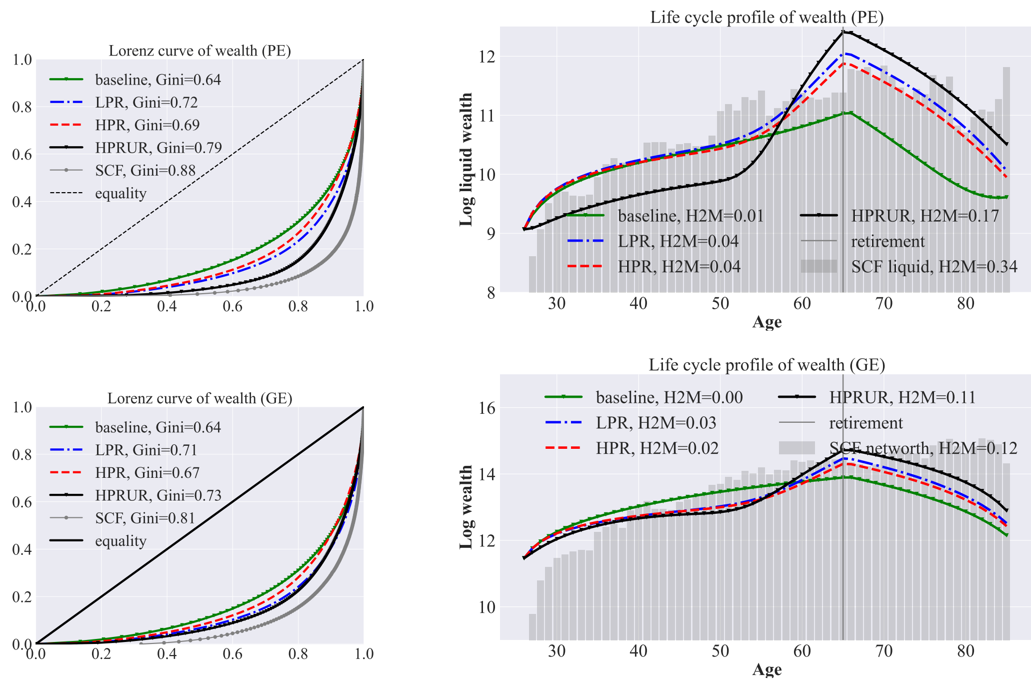
In this section, I sequentially add the following three features of PRs and show that the PR increases the wealth Gini and the fraction of the H2M agents derived from the baseline model, which are both closer to those observed in the data. The first is an average lower wage risk (*LPR*); the second is the heterogeneous perceived wage risk in addition to the average lower size risk (*HPR*); the third is the heterogeneous unemployment risk (*HPRUR*) as revealed in the perceived U2U and E2E probabilities.

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

[54]According to this definition, liquid assets include checking, savings, 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.

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 the log average wealth compared to the average net liquid wealth by age, in the 2016 *Survey of Consumer Finance* (SCF) (right), in partial equilibrium. The bottom panel shows the same figures in general equilibrium, with the total net worth in the SCF representng the measure of household wealth.

6.2.1. Lower wage risks

For the lower wage risks (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; that is, $\sigma_\psi = 0.03$ and $\sigma_\theta = 0.03$. In the meantime, I calibrate the heterogeneity in the growth rates of the 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 the yearly permanent heterogeneity $\sigma_{\xi,\psi} = 0.04$. Intuitively, this means that every year in the life cycle, agents anticipate the dispersion of a 4 percentage points standard deviation of permanent wage growth across all 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 the risks and the heterogeneity is crucial to ensuring comparability with the baseline model. Lower perceived risks and higher predictable heterogeneity are the flip sides of the same coin. Other things being equal, a smaller size of wage risk would have mechanically lowered the realized wage/income inequality in the model. For the model to still admit realistic wage inequality, as seen in the SIPP data, the differences between the baseline calibration of the risks and the lower risks need to be attributed to the unobserved heterogeneity in the wage growth rates.

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

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

6.2.2. Heterogeneous wage risks

As shown in Section 4.1, a large degree of heterogeneity in the PRs is attributable to individual fixed effects, which might reflect the true ex-ante heterogeneity in the wage risks (HPR) different individuals face beyond common observable factors. Hence, I directly calibrate the heterogeneity in the wage risks using the estimated distribution of the 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 the *PRs* to calibrate such heterogeneity. On top of the *LPR*, allowing heterogeneity in the PRs unambiguously contributes to more wealth inequality because it induces different precautionary savings 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 the experiment of the *LPR*. As a result of the two competing forces, the wealth Gini coefficients in the *HPR* actually decrease by 3-4 percentage points from the

LPR, but they both remain significantly higher than the baseline.

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

6.2.3. Heterogeneous unemployment risks

Similar to the calibration of the 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 (Krueger et al. 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 the unemployment risks, I adopt the same approach as in Section 4.3 applied to the 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 potentially long durations of unemployment with lower expected incomes and higher probabilities of hitting their borrowing constraints.

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

With the incremental improvement of the model fit, it is natural to ask about the relative importance of the various patterns of the PRs. Table 4 summarizes all of the model-implied measures and their empirical counterparts. The summary suggests that the relative importance of the wage growth rates and the unemployment risks depend on the measures of the fit. First, heterogeneous wage growth rates (in conjunction with a lower wage risk) and heterogeneous unemployment risks play equally important roles in explaining wealth inequality. The Gini coefficients for the two channels increase by about 8-10 percentage points, respectively. Second, it is the heterogeneity in the unemployment risks, instead of in the wage growth, that helps produce a more-realistic share of H2M agents. It is also worth asking where 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 rich agents or a lower share of poor agents. The location-specific wealth shares in Table 4 suggest the latter mechanism. In particular, from the baseline model to the experiment of the *HPRUR*, the wealth share of the bottom half of the agents in the economy decreases 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 of the borrowing constraint, 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 the heterogeneity in the preferences, especially in the time discount rates (Krusell and Smith 1998; Krueger et al. 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, the survey-implied heterogeneity in the risk perceptions has the advantage of being directly observable and useful in the model. This paper shows that the heterogeneity of income risks and growth rates is another observable factor that should be accounted for before attributing the unexplained wealth

[56] For instance, Epper et al. (2020) directly elicited time preferences of individuals via experiments and showed that heterogeneous preference do 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: The table shows the model-implied Gini coefficients, the wealth shares owned by the bottom 90, 70 and 50 percent of agents, the mean wealth-to-income ratio, and the shares of hands-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 the 2016 SCF.

inequality solely to the preference heterogeneity. Another advantage (not explored in this paper) is that disciplining the model with the observed heterogeneity, such as in the income risks perceived by the agents, makes the model more transparent and allows the welfare analysis to be carried out with greater clarity than in the unobserved preferences 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 the 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 degree of indirectly estimated preference heterogeneity will be less in the recalibrated model.

6.3. Subjective perceived risks

So far, all of 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 as the true model risk parameters that determine the dispersion of the income shocks—a calibration alternative to the conventional assumptions.

It is critical, however, to consider how robust the results are if we adopt a different assumption that the agents' perceived risks as reported in the survey only shape their consumption/savings decisions (as calibrated *HPRUR*) but are somehow different from the true underlying risk parameters, which objectively govern the distribution of the 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, are now both a function of the individual consumption/savings policies based on subjective risks and the objective income risks that determine the realization of the income shocks and the income distribution.

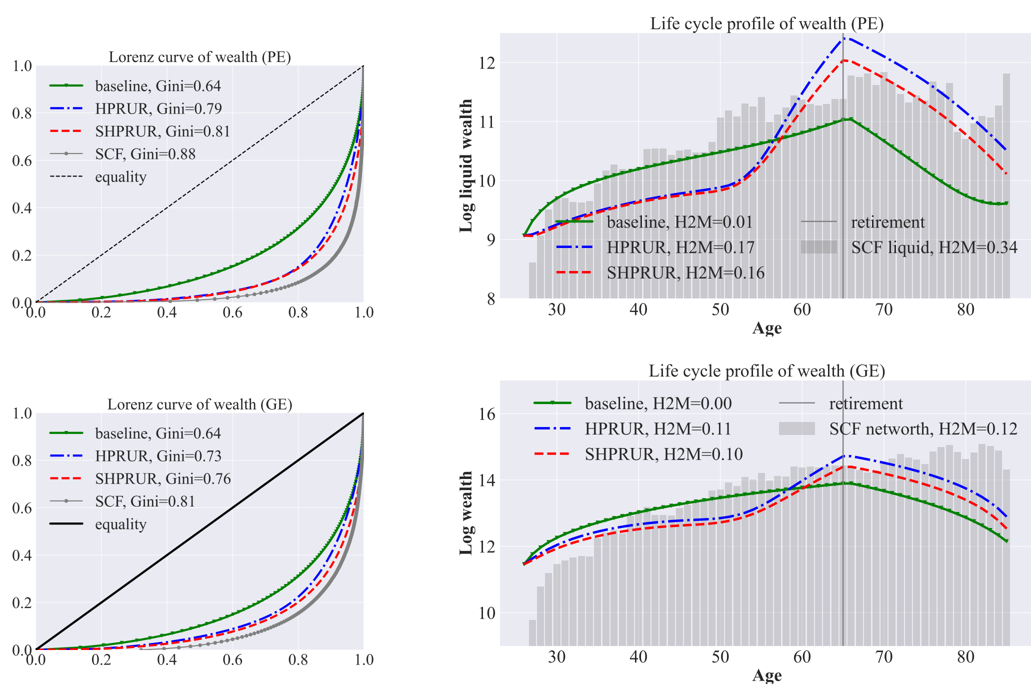
$$\tilde{\psi}_{\tau}(\tilde{B}) = \int_{\tilde{x}\in\tilde{X}} \tilde{P}(\tilde{x}, \tau - 1, \tilde{B})d\tilde{\psi}_{\tau-1} \quad \text{for all} \quad \tilde{B} \in \tilde{B}(X) \tag{26}$$

Such a model exercise is actually not just a robustness check but is also an experiment model that breaks down the model effects of the 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 the consumption/savings 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 the 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 the PE and 0.76 in the 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 savings behaviors when a heterogeneous and lower income risk profile is added to the baseline model. Meanwhile, a fraction of the H2M agents, 16% in the PE and 10% in the GE, remains similar to the objective model. The minor differences between the subjective and objective model lines suggest that it is mainly the "choice" channel, instead of the realized inequality via the "outcome" channel, that drives the results. Even if we do not 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/savings choices, this reduces the difference in the unexplained wealth inequality between the model and the 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 savings decisions are made based on such perceptions, they generate model predictions about wealth accumulation behaviors that 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 profiles of the log average wealth compared to the average net liquid wealth by age in the 2016 *Survey of Consumer Finances* (SCF) (right) in partial equilibrium. The bottom panel shows the same figures in general equilibrium, with the total net worth in the SCF as the measure of household wealth.

7. Conclusion

A large class of incomplete-market macroeconomic models that features uninsured idiosyncratic income risks and the resulting wealth inequality does not incorporate one observable dimension of the 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 those assumed through common calibration of these models and prove to be another observable factor useful for matching the model-predicted wealth inequality with the empirical patterns. Furthermore, the perceived risks are lower than the conventional estimates/calibrations, suggesting a higher degree of anticipated heterogeneity, which helps to explain why these models usually predict higher buffer stock savings than those found 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 are no longer 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 and helps economists do a better job of matching empirical patterns within the macroeconomy.

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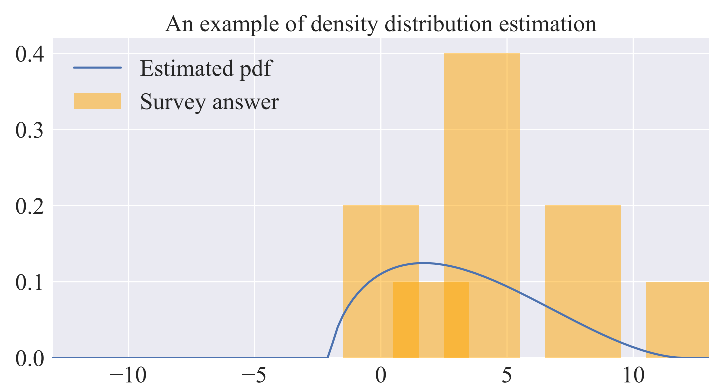
Appendix A. Online Appendix

A.1. Density estimation of the survey answers

With the histogram of the answers for each individual in hand, I follow Engelberg et al. (2009) to fit each of these answers with a parametric distribution accordingly for the three following cases (see Figure A.1 for an example). In the first case, when three or more intervals are filled with positive probabilities, these are fitted with generalized beta distributions. In particular, if there is no open-ended bin on the left or the right, then a two-parameter beta distribution is sufficient. If there is an open-ended bin with a positive probability on either the left or the right, since the lower 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, this is fitted with an isosceles triangular distribution. In the third case, if there is only one positive probability of the interval, that is, a probability equal to one, this is fitted with a uniform distribution.

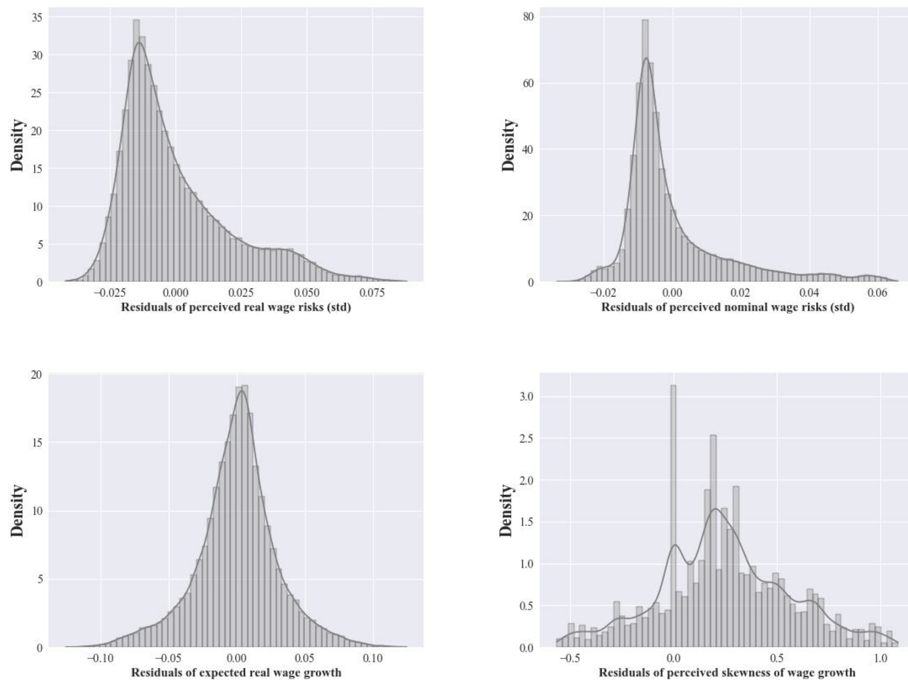
FIGURE A.1. An illustration of the density estimation of the survey answers



Note: This is one example of a bin-based forecast of the wage growth in the *Survey of Consumer Expectations* (SCE) and how it is fit by a parametric distribution. The horizontal axis shows the values of the expected wage growth and the vertical axis shows the probabilities assigned by the respondents.

For all of the moment's estimates, there are inevitably extreme values. This could be due to the idiosyncratic answers provided by the original respondents, or some non-convergence of the numerical estimation program. Therefore, for each moment of

FIGURE A.2. Dispersion in expected wage growth and perceived skewness



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

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

A.2. Other facts about perceived risks

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 the SCE.

A.2.2. Time-varying patterns of perceived risks

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 estimates of the SIPP data. Under the correct model specification and the agents' FIRE, one may expect the PRs and estimated risks to be if not equal, then to 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 risks using the SIPP, reinforcing the finding in Section 4.1. For instance, the latter, which is based on the full sample, should have a standard deviation of 10% per year, while the average earnings risk perception in the *SCE* is only 2%.

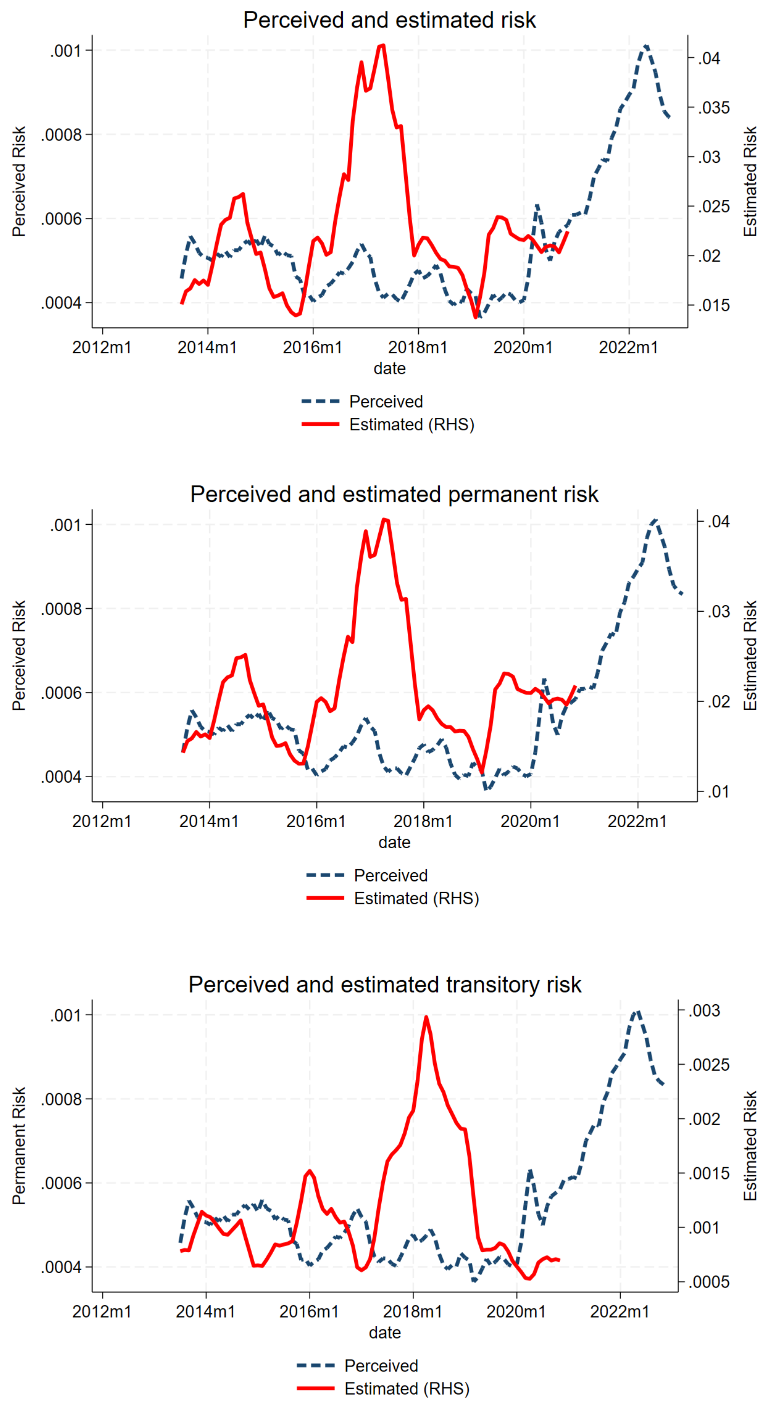
A.3. Wage risk estimation using SIPP data

A.3.1. Sample selection

To estimate the wage risks or risks to earnings, conditional on working 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 below, and these are approximately identical to those in Low et al. (2010) for computing the wage rate for the same job, using 1993 panel data from the *Survey of Income and Program Participation*.

- Time: January 2013-December 2020
- Age: 20-60 years old
- Work arrangement: employed by someone else (excluding self-employment and other work arrangements): 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 earnings 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 the individual's average wage.
- No days off without pay: EJB1_AWOP1 = 2.

FIGURE A.3. Perceived versus calibrated risks over time



Note: The figure shows 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 the SIPP and then aggregated into annual frequencies.

- Continued job spell since December of the last year: RJB1_CFLG=1.
- Drop imputed values: EINTTYPE==1 or 2.
- Drop government/agriculture jobs: drop if TJB1_IND>=9400.

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

TABLE A.1. Summary statistics of the SIPP sample

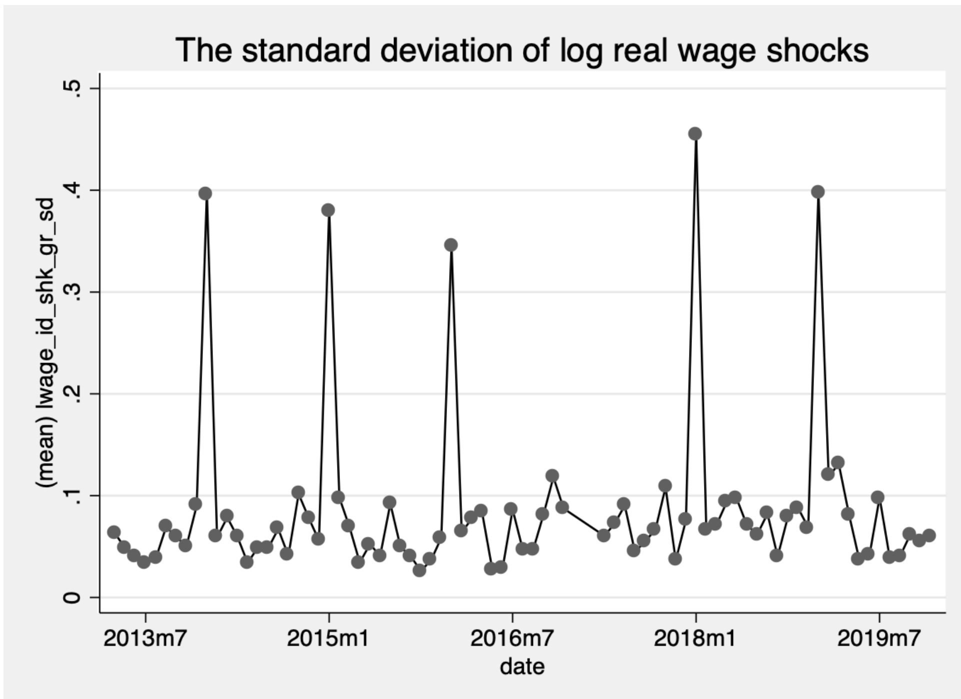
	Obs	Volatility
Year		
2013 (14%)	9,278	N/A
2014 (16%)	12,011	0.41
2015 (12%)	8,853	0.37
2016 (8%)	5,699	0.34
2017 (9%)	6,305	N/A
2018 (11%)	7,877	0.45
2019 (11%)	8,047	0.37
2020 (10%)	7,131	0.35
2021 (4%)	2,974	0.42
Education		
HS dropout (21%)	14,900	0.39
HS graduate (45%)	31,345	0.39
College/above (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 the SIPP is that it collected monthly information by surveying each correspondent every four months before the 2013 wave and once a year afterward (since the 2014 wave). This leads to the well-documented issue of the seam effect (Ryscavage 1993; Rips et al. 2003; Nekarda 2008; Callegaro 2008), which states that reported changes in survey answers are relatively small for adjacent months within a survey wave but changes are much more abrupt between months across surveys. Such a difference could be either due to the under-reporting of changes within a reference period (for reasons such as the recall bias) or the over-reporting of changes across the 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 the volatility between December and 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 the SIPP.

Due to the issue of the monthly wage volatility, for the monthly risk estimations, I exclude observations for December and January, leading to the non-identification of the risks of each January. By doing so, I basically assume that the within-wave respondents did not under-report the true changes to their wages, while the cross-wave answers over-reported these changes. But the opposite assumption might be true, in that respondents under-reported the changes within the reference year when they retroactively answered the survey questions and the changes across the reference periods were correctly

[57]Note that the only exception is for January 2017, for which no monthly growth rate is available due to the reshuffling of the SIPP sample.

reported.

One way to incorporate the cross-wage changes instead of dropping them by brutal force is to estimate the risks at lower frequencies, that is, quarterly and yearly, and to construct the quarterly/yearly periods such that these cover the cross-wave cutoff month in December.

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 the wages of individual i from $t-2$ to t, hence, three observations of the 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 risks $\sigma_{\theta,t}$ and $\sigma_{\theta,t-1}$.

Three consecutive observations of wage data are sufficient under the 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.

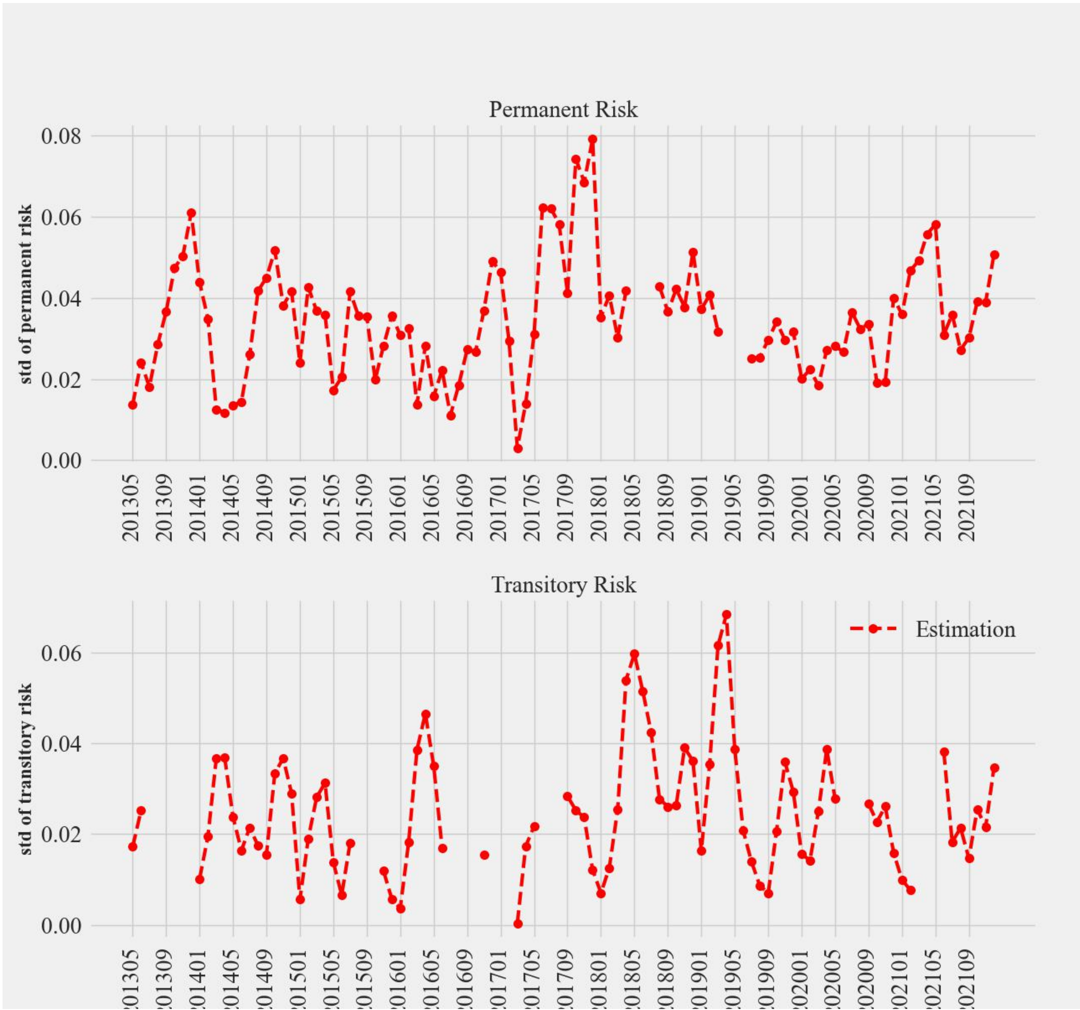
$$
\begin{aligned}
&var(\Delta w_{i,t}) = var(\psi_t + \theta_t - \theta_{t-1}) = \sigma^2_{\psi,t} + 2\bar{\sigma}^2_{\theta,t} \\
&cov(\Delta w_{i,t}, \Delta w_{i,t+1}) = cov(\Delta w_{i,t-1}, \Delta w_{i,t}) = -\bar{\sigma}^2_{\theta,t}
\end{aligned} \tag{A2}
$$

Figure A.5 plots the identified time-varying component-specific risks under a wage process set at monthly frequencies. 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 et al. (2021) shows that income dynamics at higher frequencies,

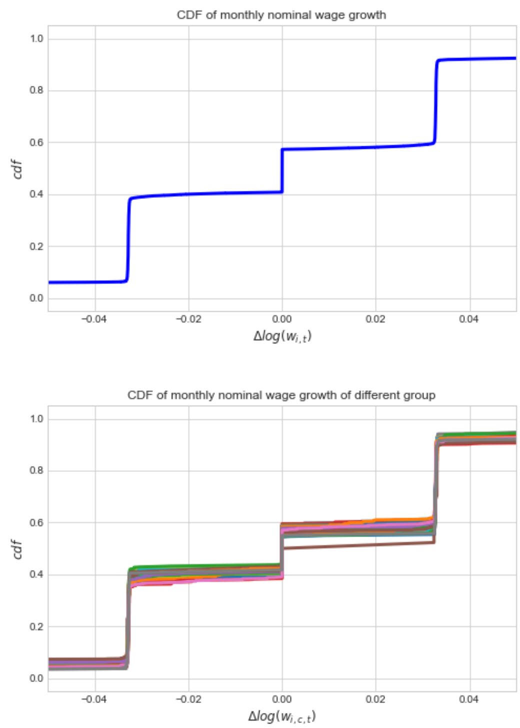
FIGURE A.5. Monthly permanent and transitory wage risks



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

that is, monthly, require modifications for such a process to be more consistent with the data. In particular, the authors allow for infrequent arrivals of both transitory and permanent shocks. The assumption of infrequent shocks is primarily motivated by the observed pattern (as confirmed in Figure A.6 using nominal wage growth in the SIPP) that a sizable mass of growth in individuals' monthly wages is concentrated around zero.

FIGURE A.6. Conditional density function of monthly wage growth



Note: The cumulative distribution function of the monthly wage growth from the SIPP for the whole sample (left) and by 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 lower frequencies, such as yearly and quarterly.

With wage growth in years 2014, 2015, 2016, and from 2018 to 2021, I can identify the year-specific permanent risks for 2014, 2015, 2016, 2018, 2019, and 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 for that year; hence, it is not possible to identify the permanent risks in 2017 and the transitory risks in its adjacent years.

The estimated sample averages are reported in Table A.2. For the years with identified risks, the estimated risks at annual frequencies seem to be much larger than those commonly seen in the literature, as summarized in Table A.3. In particular, the size of

TABLE A.2. Estimated wage risks at lower frequencies

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.

the permanent shock is estimated to be 32%, in contrast to the standard estimation of 10-15%. And the transitory risks are estimated to be around 23%, which also exceeds the standard estimates of from 10% to 20%.

A similar pattern can be seen from the quarterly estimates using quarterly growth of average wage rates (see also 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 the 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 the SCE.

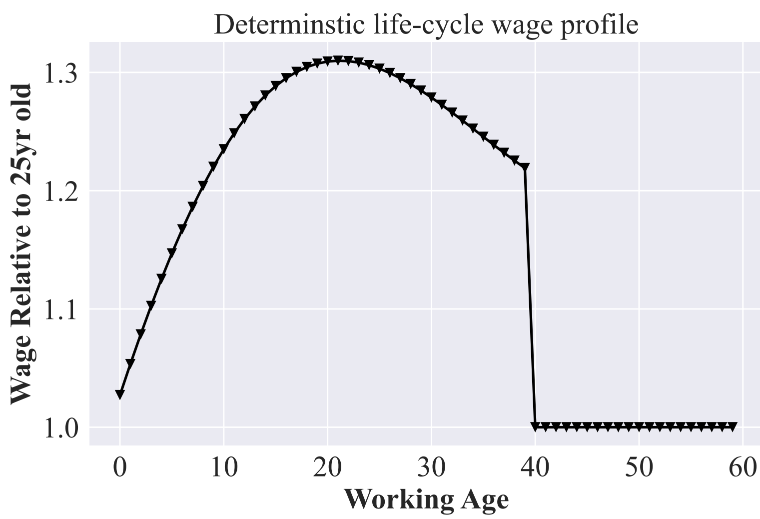
A.6. Calibration heterogeneous income risks and growth rates using the SCE

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

A.7. Income risks in the existing literature

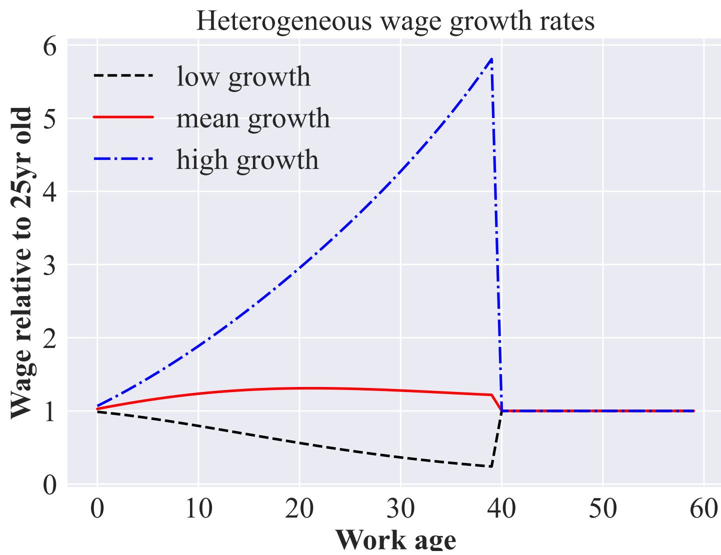
Table A.3 summarizes the most common estimates of income risks seen in the literature.

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



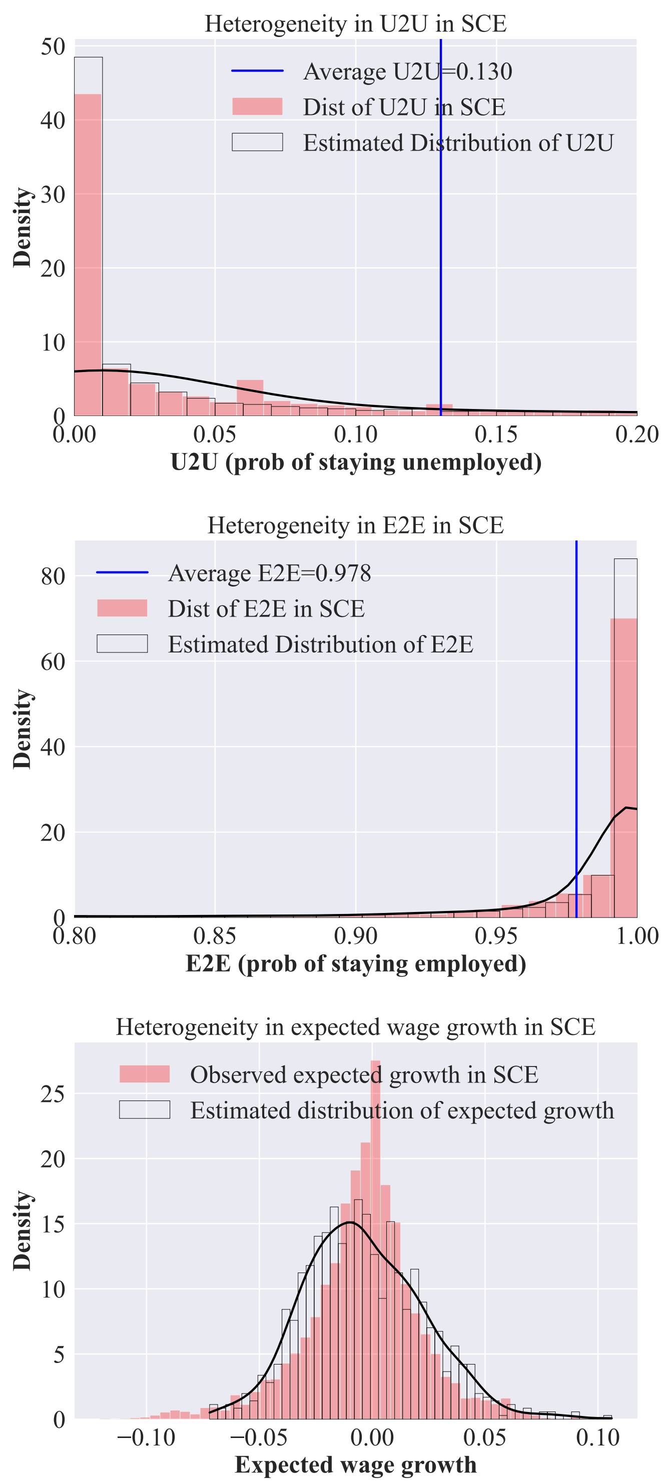
Note: This profile is used for all model calibrations. It is based on a regression of fourth-order age polynomials of the real wage from the primary jobs listed in the SIPP between 2013m3 and 2019m12, controlling for time, education, occupation, gender, etc. The post-retirement profile is assumed to 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 the *LPR*, *HPR*, and *HPRUR* models. They are calibrated to be consistent with the estimates of σ_{ξ}^{ψ}.

FIGURE A.9. Calibration of heterogeneous unemployment risks and wage growth rates from the SCE



This figure illustrates the calibration of the unemployment risks and wage growth using the *Survey of Consumer Expectations*(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 et al. (2004)	[0.094; +]	0.255	N/A	N/A	Persistent + transitory	No	Table 2
Blundell et al. (2008)	[0.1,+]	[0.169,+]	N/A	N/A	Permanent + MA	No	Table 6
Low et al. (2010)	[0.095,0.106]	0.08	0.028	N/A	Permanent+transitory with job mobility	Persistent	Table 1
Kaplan and Violante (2014)	0.11	N/A	N/A	N/A	Persistent	No	Page 1220
Krueger et al. (2016)	[0.196,+]	0.23	[0.046,0.095]	[0.894,0.95]	Persistent +transitory	Persistent	Page 26
Carroll et al. (2017)	0.10	0.10	0.07	0.93	Permanent+transitory	Transitory	Table 2
Bayer et al. (2019)	0.148	0.693	N/A	N/A	Persistent time+MA	No	Table 1
My Estimates based on SIPP	0.10	0.016	N/A	N/A	Permanent +transitory	No	Table A.1

The conservative (lower-bound) estimates/parameterizations on idiosyncratic income risks at annual frequencies, seen in the literature.