Perceived versus Calibrated Income Risks in Heterogeneous-Agent Consumption Models

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[Most Recent Draft]

Abstract

Heterogeneous-agent consumption-saving models often calibrate idiosyncratic income risk using the dispersion of unexplained income residuals, yet these estimates diverge from household perceptions. Using data from the New York Fed's *Survey of Consumer Expectations*, I directly calibrate perceived risks and find that they are substantially lower and more heterogeneous than conventionally calibrated values. This "perception wedge" stems from both unobserved heterogeneity (private knowledge regarding growth rates) and agents' overconfidence. Incorporating these subjective beliefs into a heterogeneous-agent life-cycle model significantly improves the empirical fit for wealth inequality and the share of hand-to-mouth households. The results demonstrate that the "choice channel"–where decisions are driven by subjective perceptions–is the primary driver of wealth accumulation dynamics.

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

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1. Introduction

Income risks matter for both individual behavior and macroeconomic outcomes. Given identical expected income and homogeneous risk preferences, different degrees of risk 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, based on 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]

While idiosyncratic income risks are one of the key inputs in the class of macroeconomic models featuring market incompleteness, its size and heterogeneity are not directly observable. One common practice in this literature is inferring risks from unexplained dispersion in income changes seen in panel data, and then treating the estimates as the true degree of risks as perceived 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 misspecification. Certain information, either an individual's ex-ante 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. Meanwhile, agents may subjectively perceive risks differently from their objective counterparts for various reasons, such as incomplete information and overconfidence. 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 perceived risks of labor income surveyed by the New York Fed's *Survey of Consumer Expectations* (SCE). Building on the previous work that focuses on estimating partial insurance using expectational surveys (Pistaferri 2001; Kaufmann and Pistaferri 2009), this paper uses SCE's density survey and expected job transition probabilities, which directly reveal perceived income 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. 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.

[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).

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.[5] 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. Similar to wage risks, I also found that perceptions of unemployment risk are widely heterogeneous.

The reported perceptions matter only if they are meaningfully linked to households' actual behaviors, such as consumption–and I confirm that they are. Individual-specific perceptions of risk provide ex-ante evidence of precautionary saving motives at the micro level. In particular, using SCE data, I find that an individual's expected spending growth is positively associated with their own perceived income risk, alongside other forces implied by a non-linear Euler equation. My analysis underscores that precautionary saving motives are actually better tested with ex-ante expected consumption growth instead of ex-post outcomes, and based on the same individuals' expectations instead of their indirect proxies.

Another major finding of the paper that turns out to carry rich implications is that the perceived wage 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 using the panel data of wage growths following the conventional approach is at least 10%, combining the size of the permanent and transitory shocks. 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 on wage risks, such as those by Low et al. (2010), in addition to other broader-based 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.

It is also found that the wedge between perceived and calibrated risk stems from two sources proven to be both important. The first is the unobserved heterogeneity, in that agents hold private information regarding their wage growth rate that is misattributed to shocks by econometricians. The second is overconfidence in that agents underestimate the true risks they face. In particular, up to about 4 percentage points within the wedge reflects the expected heterogeneity in yearly wage growth rates by the agents, which is potentially private knowledge to econometricians, and the rest, about 20 percentage points, reflects overconfidence. Combining survey expectations, perceived risks, and realized wage growth jointly enables one to identify these components. Intuitively, the identification relies on the fact that the expected dispersion of agents reflects heterogeneity, the unexpected dispersion reflects the true risk, and the wedge between true risk and perceived risk reveals overconfidence. I also consider the case where

[5] These patterns align well with those reported by Koşar and Van der Klaauw (2025) with perceived risks in SCE measured by IQR.

expectational dispersion of wage growth rates contains idiosyncratic biases, implying a wider expectational dispersion than the true heterogeneity. Regardless, it remains that both unobserved heterogeneity and overconfidence play a role in driving the wedge.

This evidence motivates me to utilize survey-implied risks, as what agents truly perceive, to calibrate income risks in a standard partial-equilibrium, incomplete-market, life-cycle, and one-asset consumption-saving model to quantify these effects on liquid asset accumulation and marginal propensity to consume (MPC). 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). In the preferred recalibrated subjective model, I instead use survey PRs to calibrate subjective perceived wage and unemployment risks, and also add the ex-ante different life cycle growth profiles to be consistent with the identified heterogeneity. The model is subjective in the sense that perceptions and actual income processes are separately calibrated. Compared with the baseline, the recalibrated subjective model markedly improves the match to the distribution of liquid wealth. It raises the share of households with less than half a month of income in liquid assets, the hand-to-mouth (H2M) population, from 0.01 to 0.19 (data: 0.35). It also increases the wealth Gini from 0.70 to 0.81, bringing it closer to the empirical value of 0.85. In addition, the model-implied MPCs also increase significantly by 10 percentage points to 0.26, consistent with the stated MPCs in the same survey. What is particularly notable is the life-cycle profile of H2M agents that closely mirrors the data.

Three forces together drive the model closer to the data. First, heterogeneity in perceived wage and unemployment risks increases asset inequality by inducing heterogeneity in consumption/saving choices. Second, a smaller perceived risk than in the baseline model, i.e., overconfidence, implies reduced precautionary saving motives, hence a lower level of wealth accumulation by all agents in the economy. Although it is found that this feature alone only mildly increases the H2M share in the model, its contribution compounds with incorporating the heterogeneity in growth rates and unemployment risks. Third, a lower degree of perceived risks implies a higher degree of predictable heterogeneity in wage growth, which translates to differential asset accumulations. A degree of ex-ante heterogeneity in the life-cycle permanent earning growth profiles with a dispersion of 2.8 percentage points per year, a seemingly small number, actually implies significantly increased permanent income heterogeneity in the model. This is a powerful force that widens the model's wealth distribution. [6]

Since the survey expectations on wage growth and job transitions are separately elicited, I can 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 11 percentage point increase in the wealth Gini. Meanwhile, the heterogeneity in perceived unemployment risk is the key to accounting for a larger share of H2M households being closer to the data; that is, an increase of 11 percentage points out of 18 in the share of H2M households is attributed to the realistic calibration of the heterogeneous unemployment risks. The incorporation of the two dimensions of earning risks seems to be complementary to each other.

Our benchmark subjective model deviates from the FIRE (full-information rational-

[6] This echoes several 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).

expectation) assumption in that the perceived risk determining consumption/saving decisions in the model differs from the actual income risk parameters governing draws of income shocks.[7] In alternative models, I equalize the latter to the former, treating perceived risks as the model's truth. The difference between these variants and the subjective model also reveals a breakdown of 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: no matter if the actual risks align with perceptions or the conventional calibration, letting consumption/savings decisions be driven by the survey-reported risks alone is the key 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.

Finally, the paper demonstrates that the superior fit of the subjective model is robust and often complements a range of additional features discussed in the literature. First, I consider the existence of expectational biases, which lead to dispersion in subjective life-cycle income profiles that is wider than that in their actual counterparts. Second, I allow for different subjective life-cycle unfolding patterns of growth-rate heterogeneity, assuming that agents perceive the dispersion of growth rates as monotonically increasing, decreasing, or hump-shaped over the life cycle. The main predictions of the subjective model are largely preserved under these alternative specifications. I further show that introducing preference heterogeneity—particularly non-homothetic preferences (Straub 2019)—and relaxing the zero-borrowing constraint improves the model's empirical fit. Moreover, I document that the subjective model delivers better performance across various moments when comparing preference calibrations that are indirectly inferred by targeting different sets of moments.

Related literature

This paper relates to several strands of the literature. First, following Dominitz and Manski (1997) and Manski (2004, 2018), it uses survey data to study not only subjective income expectations but also perceived income risks.[8] I compare these perceptions with income risks estimated from panel data using standard methods (MaCurdy 1982; Abowd and Card 1989; Gottschalk et al. 1994). While most of the income-risk literature focuses on the time-series, cyclical, and cross-sectional properties of estimated risks,[9] this paper emphasizes the discrepancy between perceived and indirectly estimated risks. A closely related literature studies job-separation and job-finding expectations (Stephens Jr 2004; Drahs et al. 2018; Conlon et al. 2018; Balleer et al. 2021; Mueller

[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.

[8] See Koşar and Van der Klaauw (2025) for detailed evidence on heterogeneity in perceived earnings risks using the same survey.

[9] See, among others, Meghir and Pistaferri (2004); Storesletten et al. (2004); Blundell et al. (2008); Guvenen et al. (2014); Arellano et al. (2017); Guvenen et al. (2019); Bayer et al. (2019); Guvenen et al. (2021); Bloom et al. (2018); Moffitt (2020).

et al. 2021; Mueller and Spinnewijn 2021). In particular, related to Balleer et al. (2021), which documents over-optimistic and heterogeneous job-finding beliefs, this paper studies perceived wage risks and argues that lower perceived risks may reflect not only behavioral biases, but also the presence of advance information.

The paper most closely related to this one is the contemporaneous study by Caplin et al. (2023). A key methodological difference concerns how subjective risks are compared with their conventional counterparts. Caplin et al. (2023) simulate unconditional earnings distributions from surveyed beliefs and compare them with Danish cross-sectional administrative data, whereas this paper estimates conditional income risks using standard methods and compares them with conditional risk perceptions reported in the survey. Despite these differences, both studies find that perceived earnings risks are lower than those inferred indirectly, consistent with unobserved heterogeneity and overconfidence. The two papers also differ in their quantitative frameworks: this study uses a standard life-cycle incomplete-markets model, building on Carroll et al. (2017) to study liquid wealth accumulation, while Caplin et al. (2023) adopts a search-and-matching model.

Second, this paper relates to the "insurance versus information" issue in the partial insurance literature (Pistaferri 2001; Kaufmann and Pistaferri 2009; Meghir and Pistaferri 2011; Kaplan and Violante 2010; Hendren 2017; Stoltenberg and Uhlendorff 2022). Empirical estimates of consumption insurance often conflate unanticipated income shocks with information already known to agents, leading to excess smoothness (Flavin 1988). Like this literature, I use surveyed expectations to measure agents' conditional beliefs. The key differences are that I directly use survey-reported income risks from density forecasts, rather than inferring risks from forecast errors,[10]. Also, crucially, I emphasize the survey perceptions may not only reflect superior information, but also overconfidence.

Third, this paper contributes to the literature on consumption, saving, and the macroeconomic implications of subjective income expectations. Prior work studies learning about income risk and heterogeneity in income profiles (e.g., Pischke 1995; Wang 2004; Guvenen 2007), information frictions in household expectations (Carroll et al. 2018), biased income beliefs (Rozsypal and Schlafmann 2023), and information choice in heterogeneous-agent models (Broer et al. 2021). This paper differs in two key ways: it focuses on the second moment of income, namely income risk, and it disciplines belief heterogeneity directly using survey data, remaining agnostic about the specific expectations-formation mechanism.

2. Theoretical framework

2.1. Wage process and perceived risk

To be consistent with the survey-elicited questions in the SCE, I separately focus on the wage risk conditional on employment status in this section and the risks associated with job transitions in the later section. 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)

[10]See Karahan et al. (2017) for such an exercise using SCE data.

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

There is an extensive discussion in the literature about the exact time-series nature of the stochastic component e. For instance, it may consist of both a permanent and a transitory component.[11] Or some of the literature may replace the permanent component with a stationary/persistent component in the form of an autoregressive (AR) process, as in Storesletten et al. (2004); Guvenen (2007, 2009). The transitory component could be moderately serially correlated following a moving-average (MA) process.(Meghir and Pistaferri 2004) 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 $e_{i,t}$.

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

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 $t+1$.

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

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 $e_{i,t}$.

Consider $Var^*_{i,t}(\Delta w_{i,t+1})$ as the FIRE counterpart of what this paper hereafter refers to as the subjective perceived risk (PR), which is denoted as $Var_{i,t}(\Delta w_{t+1})$ (without the superscript $*$) and is directly measured in the survey.

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 age polynomials, 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." [12]

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

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

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

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 a FIRE agent. This is primarily because econometricians who have the earnings panel data cannot always control for the "unobserved heterogeneity", either purely ex-ante or due to wage innovations at time t, that is not measured in the data.[13] This is often framed, from the point of view of the agents, as the "superior information" problem (Pistaferri 2001; Kaufmann and Pistaferri 2009). It 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, 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.[14] 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

[13] The latter possibility is particularly relevant since the ex-ante heterogeneity can often be controlled by individual fixed effects with panel data.

[14] 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.

individuals in the economy. This prevents modelers from possibly making imperfect assumptions when they estimate group-specific income risks by grouping individuals based on very limited dimensions of observable factors, such as education and age.

Importantly, for survey-reported PRs to outperform calibrated risks in predicting household behavior, it is sufficient that agents base their consumption-saving decisions on their perceptions–even if those perceptions deviate from true risks and violate FIRE, for instance, due to overconfidence. While the remainder of the paper evaluates the relevance of these assumptions, the key takeaway is that survey-based PRs, even when misaligned with objective risks, provide a better basis for predicting individual decisions than conventional calibrated risks, as long as they act upon such perceptions. This is indeed the case, as reported in Section 4.6.

3. Data, variables, and density estimation

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 of around 1,300 household heads during the period June 2013 to July 2021, or over 97 months. Respondents remain on the panel for up to 12 consecutive 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 same job at the same place for the 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%?" Respondents are asked to assign probabilities to 10 unequally spaced bins to report their subjective distribution.[15] Then, I fit the bin-based density forecast in each survey response with a parametric distribution.[16] The variance of the estimated distribution naturally represents an individual-specific perceived risk. To account for wage risk in real terms, I further add the individual-specific inflation uncertainty estimated using the same procedure and the same individual's density forecasts of inflation 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. To alleviate the concern of a correlation between wage and inflation expectations, I restrict our sample of analysis to before March 2020, excluding the periods of the COVID-19 pandemic and subsequent inflation surge in the United States. Arguably, with low and stable inflation in this sample period, the correlation between the two was much weaker.[17] In addition, 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

[15] 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.

[16] 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.

[17] Several papers found very limited pass-throughs from inflation expectations to wage/income expectations of individual households, such as Jain et al. (2024) and Hajdini et al. (2025). Particularly relevant is Koşar and Van der Klaauw (2025), who found that in SCE density-forecast based inflation uncertainty is weakly correlated with earning uncertainty.

be conditional on the same job position, the same hours, and the same location, this can be best 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 earnings due to 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 and other variations 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 (Low et al. 2010), major job transitions are often an important source of income risks that individual workers face. In Section 4.5, I separately examine unemployment risk expectations, surveyed as perceived job-separation and finding probabilities in the SCE.[18]

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).[19] 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.[20] 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 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

[18]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 their paper, I separately explore wage distribution conditional on staying in the same job and having the same job-transition probabilities.

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

[20]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.

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. First pass: perceived risk versus wage volatility

As a starting point, I first empirically compare the conditional perceived risks in SCE with the unconditional wage volatility from SIPP. The former corresponds to the $Var_{i,t}(\Delta w_{t+1})$ as defined in Section 2. The latter corresponds to the wage volatility $Var_c(\Delta \hat{e}_{i,t+1})$. Here, we treat each group c as a particular individual. So the wage volatility is essentially the variance across multiple years of wage growth realizations of the same worker. Figure 1 plots the distribution of the PRs across individuals and the distribution of wage volatility at the individual level that can be explained by observable demographic variables such as age, gender, and education.

The first apparent pattern from the figure is that PRs are concentrated at a much lower range of values around (2-4%) while, in contrast, the average predictable size of the wage volatility falls in the range of 25-30%. This indicates that across all workers, the realized year-over-year wage growth fluctuates at a much bigger magnitude than perceived by workers, conditional on their respective information set.[21]

Given the discussion in Section 2, it is not surprising that perceived risks are lower than the wage volatility estimates since the latter is *unconditional*. However, we show in the following sections that the perceived risks remain well below the often used "calibrated risk", which are econometricians' proxies for the *conditional* risk from the point of view of the agents.

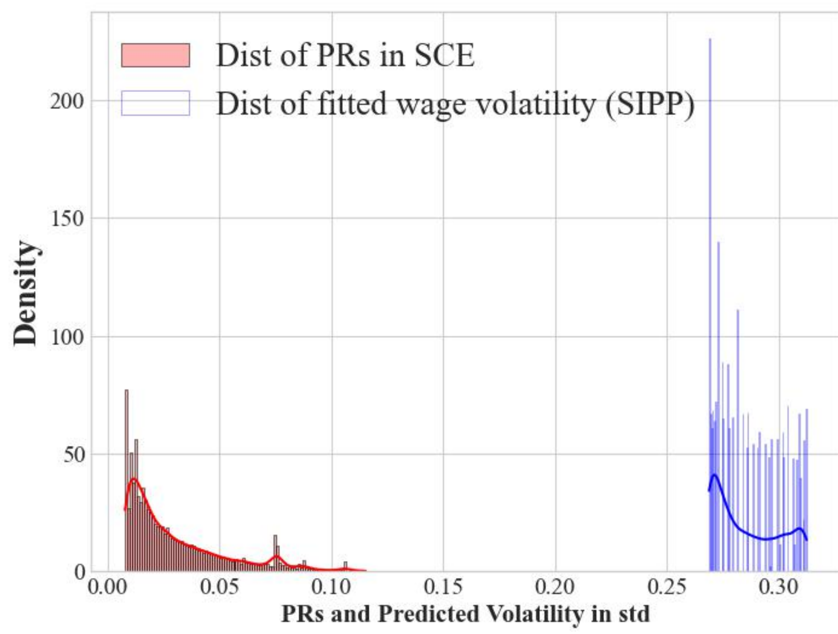
The second pattern in Figure 1 is that PRs display much greater heterogeneity than the dispersion of wage volatility explained by observables. As the figure shows, the distribution of PRs is substantially wider than the explainable component of individual wage volatility. This indicates that assuming wage volatility heterogeneity arises only from observed factors understates the full variation in perceived risks. Because wage volatility is the upstream input to risk calibration, this limited heterogeneity also carries over to the calibrated risks.

4.2. Calibrated risk based on decomposed shocks of different persistence

As previewed in Section 2, the calibrated risk estimated from realized panel data depends on assumptions made on the time-series properties of the wage shocks. Realized permanent (or persistent) shocks carry implications for future wages, whereas purely transitory shocks do not. Consequently, agents perceive different levels of risk depending on the nature of the shock. This distinction is essential for making a meaningful

[21] In the Appendix A.6, I validate this pattern with an alternative approach: comparing simulated wage growth rates based on density forecasts in SCE with the wage growth distribution in SIPP. The former has a significantly smaller dispersion than the latter, consistent with the finding here.

FIGURE 1. Dispersion in the perceived wage risk versus wage volatility



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

comparison between survey-reported perceived risks (PRs) and risks calibrated using standard econometric approaches.

To proceed, I adopt a wage process commonly used in a large body of literature. [22] 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}(consistent with the specification in Equation 17.)

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

Under this specific wage process, the PRs of an FIRE agent are equal to the sum 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.

Given this process, the calibrated risk, denoted as $\widehat{PR}$, is equal to the sum of the *estimates of* the permanent and transitory risks, $Var_t(\Delta \hat{e}_{i,t}) = \hat{\sigma}^2_{\psi} + \hat{\sigma}^2_{\theta}$. To obtain its magnitude, I follow the same generalized-method-of-moment (GMM) estimation procedure as in the literature [23] to identify the time-averaged variances of the permanent and

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

[23] 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

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.[24]

Table 1 reports group-specific estimates of total, permanent, and transitory wage risks from the wage panel, together with the corresponding average and median perceived risks. The estimated permanent wage risk, $\hat{\sigma}_{\psi}$, is about 10%, closely matching Low et al. (2010), who focus on wage rates of job stayers, excluding job-switching and unemployment spells. They likewise report annual permanent and transitory risks of roughly 10%. By contrast, my estimated transitory shocks are much smaller—below 3 percentage point—compared with the 10+ percentage point figures commonly cited based on changes in income/earnings at the annual frequency. This discrepancy mainly reflects my assumption of a higher frequency of shocks.[25] While the appropriate specification of high-frequency wage or income processes remains an active research question (Crawley 2019; Druedahl et al. 2021), I adopt these estimates as calibration benchmarks. They provide a conservative lower bound against which perceived risks (PRs) can be meaningfully compared.

4.3. Perceived risks are heterogeneous

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.[26] 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 cross-sectional differences in the PR can not be explained by observables. Furthermore, even in those observable dimensions, the group heterogeneity seen in the PR does not coincide with that seen in the estimated risks.

Figure 2 plots the group average of the PRs (both in real and nominal terms), and the calibrated risk, $Var_{i,t}(\Delta\hat{e}_{i,t+1})$, based on an estimation of the specified wage process 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 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 shows a monotone pattern over the life cycle.[27] In contrast, perceived risks almost

differences depending on the model specification.

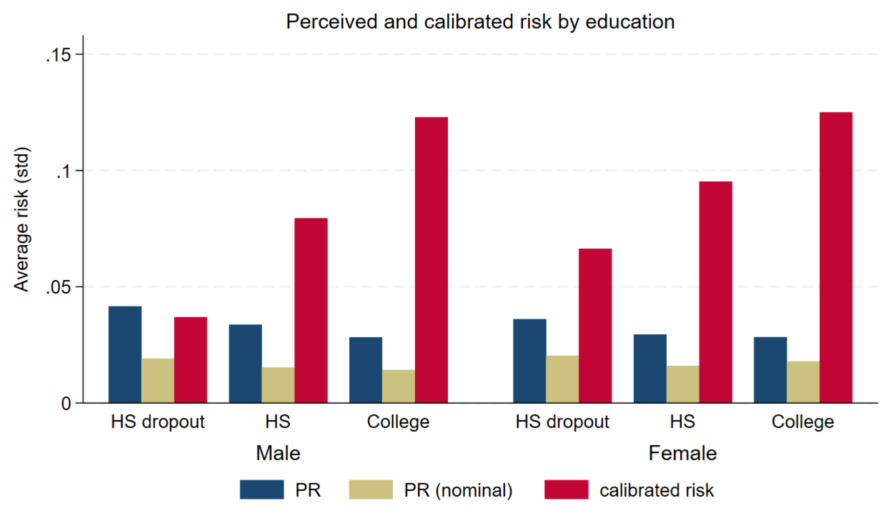
[24] I treat the annual wage as the *average* of monthly wage rates. With this, for the permanent component, the annual risk is the 4.51 times of the average monthly permanent risks over the next 12 months. The transitory risk in annual frequencies is the average of the monthly risks over the next 12 months. Appendix A.4.2 provides the derivations for this result. Appendix A.4.3 provides alternative estimates for the quarterly and yearly frequencies.

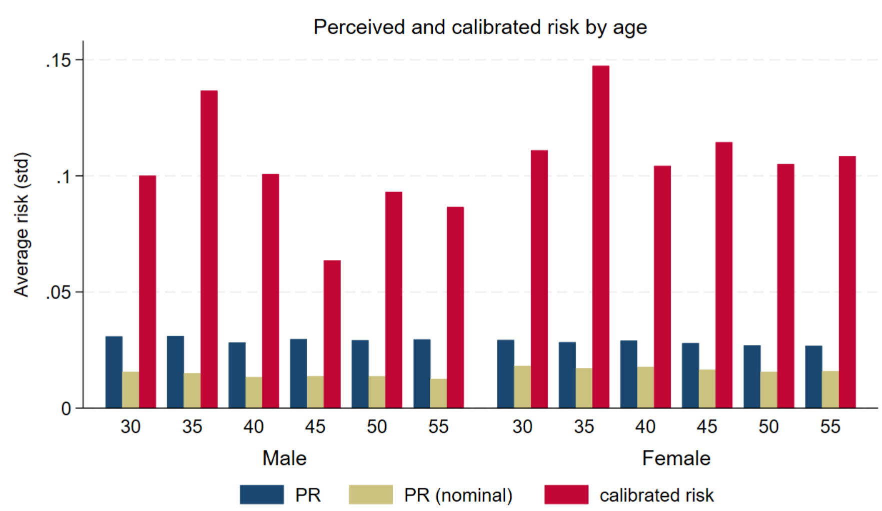
[25] Consequently, volatility inferred from annual wage growth is not directly comparable to the sum of calibrated permanent and transitory components.

[26] 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.

[27] The homogeneous age pattern of the wage risk is not necessarily contradictory with the well-

FIGURE 2. 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), and calibrated wage risk (from the SIPP) of each education-gender (upper panel) or age-gender (bottom panel) group. 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.

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.

Even though PRs do differ between observed dimensions, such factors turn out to be unable to explain the majority of the cross-sectional dispersion in PRs. In particular, the R^2 of a regression of the PR on all of the observable factors in the SCE, without the individual fixed effects, is at most 10%, while including the fixed effects increases the R^2 to 70%.[29]

This finding has two implications. First, the role of the within-group heterogeneity suggests that the conventional practice of estimating and modeling income risks as only differing by several observable dimensions fails to capture the dominant fraction of variations across individuals in wage risks. 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.

4.4. Perceived risks are lower than calibrated risks

Another salient fact is that the PR is always *smaller* than the calibrated wage risk, as shown in Figure 2. In particular, the calibrated risk of different groups falls in the range of 4-14% per year in standard deviation units. 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, while the calibrated risk of the same group is above 9-10%.

Table 1 further confirms that within each group, the perceived risks (PRs) are systematically lower than the calibrated risks, even if the latter are economists' attempted proxy for the perceived risk. In addition, Figure **??** 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.

One natural explanation for this disconnect between perceived and calibrated risks seems to be unobservable heterogeneity or superior information. However, there is another possibility: agents may underperceive the true risks they face, therefore rendering PRs to be lower than the calibrated risk, even if the latter perfectly represents the conditional risk assessment of the agents under FIRE. Can we distinguish the two explanations? The next section delves into this question.

4.4.1. Unpacking the gap: unobserved heterogeneity or overconfidence

In this section, I present a framework to account for the gap between perceived risk and calibrated risk, and also empirically identify them. Let us assume that the observed residual change in wage $\Delta\hat{e}_{i,t}$ by econometricians consists of two components. The first component $\Delta e_{i,t}$ is the truly unexpected wage shock to the agent. The second one

documented declining pattern estimated using data on household income or total earnings[28]. 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.

[29] 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.

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 square roots of the mean and median PRs ($Var_{i,t}(\Delta w_{i,t+1})$), the estimated annual wage volatility ($Var_c(\Delta w_{i,t+1})$) for each group c, the calibrated risks ($\hat{\sigma}^2_{\psi} + \hat{\sigma}^2_{\theta}$), and the calibrated risks of the permanent ($\hat{\sigma}^2_{\psi}$) and transitory ($\hat{\sigma}^2_{\theta}$) wage components for different groups. Note that the calibrated risks are annualized based on estimates from monthly wage changes. See Table A.2 for calibrated risks with annual wage growth.

$\xi_{i,t}$ is an anticipated component by the agent at $t-1$ before its realization, but cannot be observed by econometricians. $\xi_{i,t}$ could stem from unconditional heterogeneity in wage growth rates across individuals that is private knowledge, or due to innovations to i's wage growth between $t-1$ to t that enter the information set of i.[30]

$$\Delta\hat{e}_{i,t} = \Delta e_{i,t} + \xi_{i,t} \tag{6}$$

To be consistent with the wage processes in the previous section, we also assume $\xi_{i,t}$ has the same time series property as $\Delta e_{i,t}$, consisting of a permanent component and a *change* in the transitory component.[31]

$$\xi_{i,t} = \xi^{\psi}_{i,t} + \Delta\xi^{\theta}_{i,t} \tag{7}$$

A good example of $\xi^{\psi}_{i,t}$, namely the individual-specific expected innovation to the permanent wage rate, 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 unlikely to be observable by researchers, is the future earning cut to a professor who expects to be on sabbatical leave for one semester.

To the extent that the respective components in $\Delta e_{i,t}$ and $\xi_{i,t}$ share the time-series property, and they look identical to econometricians, it is easy to show that the common moment-based estimation as done in Section 4.2[32] would yield a calibrated risk $Var_{i,t-1}(\Delta\hat{e}_{i,t}) = \hat{\sigma}^2_{\psi} + \hat{\sigma}^2_{\theta}$ that differs from the PR under FIRE by exactly the size of the

[30]Since this is the heterogeneity in the growth rate, even estimating individual fixed-effects on panel records of individual income would not uncover such unobserved heterogeneity.

[31]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.

[32]See Appendix A.4.1 for more details of the estimation.

variance of $\xi_{i,t}$.[33]

$$Var_{i,t-1}(\Delta\hat{e}_{i,t}) = Var^{*}_{i,t-1}(\Delta e_{i,t}) + \underbrace{\sigma^2_{\xi}}_{=\sigma^2_{\xi,\psi}+\sigma^2_{\xi,\theta}} \tag{8}$$

Except for the special case absent unobserved heterogeneity, i.e., $\sigma^2_{\xi} = 0$, the calibrated risk $Var_{i,t-1}(\Delta\hat{e}_{i,t})$ is certainly greater than the PR under FIRE $Var^{*}_{i,t-1}(\Delta e_{i,t})$.

Another possibility that rationalizes a lower PR than calibrated risk is that the perceived risk in the data $Var_{i,t}(\Delta e_{i,t+1})$ is smaller than $Var^{*}_{i,t-1}(\Delta e_{i,t})$ due to overconfidence, denoted by δ^2.

$$Var_{i,t-1}(\Delta e_{i,t}) = Var^{*}_{i,t-1}(\Delta e_{i,t}) - \delta^2 \tag{9}$$

Combining Equations 8 and 9 yields the following relationship between calibrated risk and survey-based PR— the two have a wedge that stems from either unobserved heterogeneity or overconfidence.

$$\underbrace{Var_{i,t-1}(\Delta\hat{e}_{i,t})}_{\text{Calibrated risk } \widehat{PR}} = \underbrace{Var_{i,t-1}(\Delta e_{i,t})}_{\text{Perceived risk } PR} + \delta^2 + \sigma^2_{\xi} \tag{10}$$

Without information in addition to the calibrated risk and perceived risk, one would be unable to separately identify the contribution of σ^2_{ξ} and δ^2. This is when the heterogeneity in reported expectations of wage growth $\mathbb{E}_{i,t-1}(\Delta w_{i,t})$, the cross-sectional dispersion of the first moment of the individual-specific wage growth distribution in SCE, becomes useful. It provides an additional source of identification. Conditional on information as of $t-1$, the individual's expected wage growth rate $\mathbb{E}_{i,t-1}(\Delta w_{i,t})$ under FIRE is equal to $\xi_{i,t}$, as the $\mathbb{E}^{*}_{i,t-1}(\Delta e_{i,t}) = 0$.

$$\mathbb{E}^{*}_{i,t-1}(\Delta w_{i,t}) = \xi_{i,t} \tag{11}$$

Under the assumption that reported expected wage growth $\mathbb{E}_{i,t-1}(\Delta w_{i,t}) = \mathbb{E}^{*}_{i,t-1}(\Delta w_{i,t})$, meaning that the individual i is aware of $\xi_{i,t}$ and there is no additional bias in expectations, the cross-sectional variance of expected wage growth rates across individuals identifies the variance of $\xi_{i,t}$.[34] Intuitively, this means that if the respondents in SCE do have private information in their wage growth rates, such private knowledge should also be reflected in their expectations about future wage growth.

[33] To see this, rewrite $\Delta\hat{e}_{i,t} = \psi_{i,t} + \xi^{\psi}_{i,t} + \Delta\theta_{i,t} + \Delta\xi^{\theta}_{i,t}$, where the first two components combined are what econometricians would think as a permanent shock to the wage and the latter two combined are the transitory shock. Then the respective risk estimates of the permanent and transitory shocks, namely $\hat{\sigma}^2_{\psi}$ and $\hat{\sigma}^2_{\theta}$, are upward biased relative their true counterparts, σ^2_{ψ} and σ^2_{θ}, by exactly $\sigma^2_{\xi,\psi}$ and $\sigma^2_{\xi,\theta}$, which represent the variance of $\xi^{\psi}_{i,t}$ and $\xi^{\theta}_{i,t}$, respectively. The Equation 8 follows when we define $\sigma^2_{\xi} = \sigma^2_{\xi,\psi} + \sigma^2_{\xi,\theta}$.

[34] More generally, if individuals' reported expected wage growth rates contain biases, then the expectation dispersion reveals only an upper bound of the size of the heterogeneity.

$$\sigma^2_{\xi} = Var(\mathbb{E}^*_{i,t-1}(\Delta e_{i,t})) \tag{12}$$

In SCE, the cross-sectional standard deviation of reported expectations of wage growth is 0.04, as plotted in Figure 4D. It directly gives an estimate of σ_{ξ} taking the same value. This implies, for each year, an average 4 percentage point dispersion across agents in their expected wage growth rate that might have to do with their private information, in the absence of expectational biases. With the σ_{ξ} identified, we can attribute the remaining wedge between calibrated and perceived risk in Equation 10 to the role of overconfidence δ^2.

We have reported benchmark wage risk estimates of $\sigma_{\psi} = 0.15$ and $\sigma_{\theta} = 0.15$ (used to calibrate the baseline model in Section 5), hence a conventionally calibrated risk $\widehat{PR} = 0.21$ (in standard deviation units), the identification procedure yields the estimated unobserved heterogeneity $\sigma_{\xi} = 0.04$ and an overconfidence of $\delta = 0.20$. Correspondingly, the true risks σ_{ψ} and σ_{θ} are 0.147, slightly lower than the calibrated risks because the latter misattributes heterogeneity to risks. [35] The estimates imply that a significant portion of the differences between calibrated risk and PR is due to agents underestimating the true risks, such as overconfidence.

The estimated heterogeneity in wage expectations, σ_{ξ}, corresponds to a 4-percentage-point dispersion in expected wage growth and comprises both permanent and transitory components, $\sigma_{\xi,\psi}$ and $\sigma_{\xi,\theta}$. The extent of the permanent component crucially determines how heterogeneous life-cycle wage paths are across individuals. For example, even if only half of the total dispersion-about 2.8% per year—is due to permanent heterogeneity $\sigma_{\xi,\psi}$ that accumulates into lifetime permanent earnings, then the implications for earning profiles are large: an individual in the top third of the income distribution reaches a peak earning level around eight times their wage at age 25, whereas an individual in the bottom third, at their trough, earns only about half of their initial wage. In Section 5, I use this magnitude to calibrate heterogeneous wage growth paths, which are depicted in Figure A.7B.

One potential concern with my estimates is that the expectations $\mathbb{E}_{i,t-1}(\Delta e_{i,t})$ may contain idiosyncratic biases unrelated to true expectations. Formally, we can write

$$\mathbb{E}_{i,t-1}(\Delta e_{i,t}) = \mathbb{E}^*_{i,t-1}(\Delta e_{i,t}) + \varepsilon_{i,t} \tag{13}$$

where $\varepsilon_{i,t}$ captures individual bias. In this case, the estimate of σ^2_{ξ} is upward biased by exactly the variance of these biases. However, since the dispersion of expected wage growth in the data is at most 4%, the magnitude of such biases is likely negligible. Correcting for them would in fact raise the implied level of risk relative to the baseline estimates, and would point to an even greater degree of overconfidence.

4.5. 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

[35] Using the wage risk estimates of Low et al. (2010), $\sigma_{\psi} = 0.10$ and $\sigma_{\theta} = 0.09$, or an implied calibrated risk $\widehat{PR} = 0.135$, yield smaller estimates of overconfidence $\delta = 0.13$. Actual risks are σ_{ψ} and σ_{θ} should be 0.096.

labor income.(Low et al. 2010; Davis and Von Wachter 2011) In addition, unemployment risks are usually another central input of incomplete-market macroeconomic models. (See Krueger et al. (2016); Bayer et al. (2019) among others.) 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.[36] 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 of perceptions and realizations across different horizons, I cast both probabilities into a continuous-time rate for a Poisson point process. [37] Figure 3 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[38] 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.

4.6. Perceived income risk and consumption spending

In this section, we show that perceptions of risks do affect saving behaviors. 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 specific perceived risks and consumption plan, as documented in the SCE, provides a rare opportunity to resolve this problem.[39] This contrasts with the best practice to date, which is to impute

[36] 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.

[37] 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 $-log(1-P(ue_{t+1}|e_t))$.

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

[39] Guiso et al. (1992) provides 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,

FIGURE 3. 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.

ex-ante unemployment risks to a particular individual based on only several 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, perceived wage risk, and unemployment risks under a range of specifications.

$$(14)\quad \mathbb{E}_{i,t}(\Delta c_{i,t+1}) = u_0 + u_1\mathbb{E}_{i,t}(\Delta w_{i,t}) + u_2\text{Var}_{i,t}(\Delta w_{i,t+1}) + u_3\text{Prob}(U_{i,t+12}) + \xi_{i,t}$$

In the past, the literature operated 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

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.

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 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, perceived unemployment risk, measured by the perceived probability of job separation in the next 12 months, is significantly and negatively correlated with expected consumption growth. This is sensible, as a higher perceived risk of unemployment not only increases the dispersion of future income outcomes but also lowers expected income. While controlling perceived unemployment risk in Column (5) in Table 2, the coefficients of expected wage growth and perceived risk remain significant. This suggests the effects of both wage risks and unemployment risk perceptions on consumption/saving decisions of households, an approach pursued by this paper.

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***	0.193***
	(0.0825)	(0.0828)	(0.0334)	(0.0334)	(0.0352)
Perceived wage risk	6.127***	6.185***	2.096***	1.711***	2.006***
	(1.163)	(1.165)	(0.439)	(0.442)	(0.448)
Perceived UE risk next 12m					-0.0635**
					(0.0222)
R-squared	0.000939	0.00318	0.953	0.953	0.959
Sample Size	56046	56046	56046	56046	51155
Time FE	No	Yes	No	Yes	Yes
Individual FE	No	No	Yes	Yes	Yes

Note: regression results of expected spending growth on perceived income risks, corresponding to Equation 14. Standard errors are clustered by household. *** p<0.001, ** p<0.01 and * p<0.05.

5. Perceived risks and wealth inequality

Section 4.6 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 life cycle 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. A life-cycle consumption/saving model

I reproduce a standard incomplete-market life-cycle model of consumption and saving featuring idiosyncratic income risks. All of the direct implications of perceived risks regarding liquid wealth accumulation and wealth inequality are sufficiently conveyed in the partial equilibrium. In Section A.10 in the Appendix, I consider the general equilibrium forces as in 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 works 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, and faces a constant survival probability $1 - D$. 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. Household's problem

Each period in life, the consumer chooses consumption to maximize their expected life-cycle utility under a discount factor β and a constant survival probability $1 - D$.

$$\max_{\{c_{i,\tau}\}_{\tau=1,2...L}} \quad \mathbb{E}\left[\sum_{\tau=1}^{\tau=L}(1-D)^{\tau-1}\beta^{\tau-1}u(c_{i,\tau}) + (1-D)^{L-1}\beta^{L-1}\phi u(a_{i,L})\right] \tag{15}$$

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 $a_{i,L-1}$, scaled by a strength parameter ϕ.

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.

$$\begin{aligned}
a_{i,\tau} &= m_{i,\tau} - c_{i,\tau} \\
b_{i,\tau+1} &= a_{i,\tau}R \\
m_{i,\tau+1} &= b_{i,\tau+1} + (1-\lambda)(1-\lambda_{SS})y_{i,\tau+1} \\
a_{i,\tau} &\geq 0
\end{aligned} \tag{16}$$

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.[40] Specifically, $y_{i,\tau}$ is a multiplication of the idiosyncratic wage rate[41] $w_{i,\tau}$ 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, which is normalized to one.

$$
\begin{aligned}
y_{i,\tau} &= e^{w_{i,\tau}} W \\
e^{w_{i,\tau}} &= e^{p_{i,\tau}} \xi_{i,\tau}
\end{aligned}
\tag{17}
$$

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 $\mathbb{G} = \{G_\tau\}_{\tau=1...L}$.

$$
e^{p_{i,\tau}} = G_\tau e^{p_{i,\tau-1}} e^{\psi_{i,\tau}}
\tag{18}
$$

The persistent/transitory shock $\xi_{i,\tau}$ takes different values depending on the employment status $\nu_{i,\tau}$, which is e when employed and u when unemployed.

$$
\xi_{i,\tau} = \begin{cases} e^{\theta_{i,\tau}} & \text{if} \quad \nu_{i,\tau} = e \quad \& \quad \tau \leq T \\ \zeta & \text{if} \quad \nu_{i,\tau} = u \quad \& \quad \tau \leq T \\ \mathbb{S} & \text{if} \quad \tau > T \end{cases}
\tag{19}
$$

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_ψ and σ_θ, respectively, as well as the transition probabilities of the job spells. For both types of wage shocks, we assume normal distributions.[42]

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

[41] 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.

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

(20)
$$\psi_{i,\tau} \sim N(-\frac{\sigma^2_{i,\psi}}{2}, \sigma^2_{i,\psi})$$
$$\theta_{i,\tau} \sim N(-\frac{\sigma^2_{i,\theta}}{2}, \sigma^2_{i,\theta})$$

The transition matrix between unemployment ($\nu_{i,\tau} = u$) and employment ($\nu_{i,\tau} = e$) is the following.[43]

(21)
$$\pi(\nu_{i,\tau+1}|\nu_{i,\tau}) = \begin{bmatrix} \mho_i & 1-\mho_i \\ 1-E_i & E_i \end{bmatrix}$$

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.

Crucially, note that all income risk parameters—σ_ψ, σ_θ, $\mho$, and E—carry a subscript i, indicating they may vary across individuals. The focus of this paper is to capture such heterogeneity, as reflected in the dispersion of perceived risks, rather than to follow the common practice of assuming homogeneous risks. This approach also avoids restricting heterogeneity in income risks to a single observable dimension, such as 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.

(22)
$$V_\tau(\nu_{i,\tau}, m_{i,\tau}, p_{i,\tau}) = \max_{\{c_{i,\tau}, a_{i,\tau}\}} \quad u(c_{i,\tau}) + \phi u(a_{i,\tau})$$

(23)
$$V_\tau(\nu_{i,\tau}, m_{i,\tau}, p_{i,\tau}) = \max_{\{c_{i,\tau}, a_{i,\tau}\}} \quad u(c_{i,\tau}) + (1-D)\beta \mathbb{E}_\tau \left[V_{\tau+1}(\nu_{i,\tau}, m_{i,\tau+1}, p_{i,\tau+1})\right]$$

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 ($\mho = 1 - E$).[44]

Under homogeneous risks, the solution to the 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. With ex-ante heterogeneity in income risks, such optimal behaviors further vary across potentially individual-specific perceived risks, accordingly.

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 $\mu_{\tau+1} = \frac{(1-D)}{1+n}\mu_\tau$

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

[44]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).

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.[45]

5.1.4. Stationary distribution

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, $\psi_\tau(B)$ represents 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.

$$\psi_\tau(B) = \int_{x\in X} P(x, \tau - 1, B)d\psi_{\tau-1} \quad \text{for all} \quad B \in B(X) \tag{24}$$

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.[46]

5.2. Baseline calibration

Calibrated 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.

Despite the disagreement in these estimates, the income risks used in these models are constantly larger than those reported in the survey. This is presumably true for the risk that is most comparable to the surveyed PRs, as estimated by the wage risk in 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 $E = 0.96$.

Life cycle. The model is set at the yearly frequency. 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 earning profile over the life cycle, $\mathbb{G}$, I draw on an age polynomial regression of the log total wage income from the SCF households aged 25-65. Using total wage income for the deterministic profile, rather than relying solely on wage rates from the primary job, naturally accounts for the deterministic profile of working hours over the life cycle. The estimated profile is very similar to those obtained by Gourinchas and Parker (2002), Cagetti (2003), and Kaplan and Violante

[45] 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).

[46] In the model computation, the P functions correspond to age-specific transition matrices over a finite number of discretized grids of multiple state variables. The age-specific distributions $\psi_\tau(B)$ are generated from forward iterations of multiplying the distribution of agents at age $\tau - 1$, namely $\psi_{\tau-1}$, by the transition matrix of that age τ.

(2014). The estimated growth profile is plotted in Appendix A.6. For the retirement phase, I assume a one-time drop of 50% in the permanent wage at age 66; that is, $G_{41} = 0.5$, 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.

As to the public insurance policies, as in Krueger et al. (2016), the unemployment insurance replacement ratio is set to be $\zeta = 0.15$. (Appendix A.4 shows that under more generous replacement ratios, the subjective model still significantly improves the model's empirical fit than the baseline.) The pension income relative to permanent income is assumed to be $\mathbb{S} = 60\%$. This, plus the 50% drop in permanent income, gives an effective deterministic wage drop of 70% 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.

Initial conditions. Assumptions about the cross-sectional distribution of the initial permanent income 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 wage income at age 25 from the SCF. The normalized bank balance at the beginning of a working life is set to 0.10, which is equal to the average liquid wealth-to-income ratio at age 25 in the SCF.

Preference. The coefficient of relative risk aversion ρ is 2. The discount factor β is set to be 0.96. 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.[47] I turn to the approach of indirectly inferring preference parameters to match data moments in Section 6.4.3.

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 and liquid-assets model. (Kaplan and Violante (2022)).

6. Model results

6.1. Baseline model with calibrated income risks

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 $\sigma_\psi = 0.15$ and $\sigma_\theta = 0.15$, and unemployment risks of $U2U = 0.18$ and $E2E = 0.96$, the baseline of Figure 5 reproduces the well-known result[48] that a carefully calibrated standard one-asset incomplete-market model without additional heterogeneity, such as that in time discount rates, predicts significantly less wealth inequality (a Gini coefficient

[47] Kaplan and Violante (2022) discusses 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 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).

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

TABLE 3. Parameters for the baseline model

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
life cycle	$\mathbb{G}$	Figure A.7A	Estimated using wage inc. in 2016 SCF
preference	ρ	2	Standard calibration
preference	β	0.96	Standard calibration
bequest	ϕ	1.0	Standard calibration
policy	$\mathbb{S}$	0.65	U.S. average
policy	λ	N/A	Endogenously determined
policy	λ_{SS}	N/A	Endogenously determined
policy	ζ	0.15	U.S. average

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

of 0.70) than that in the liquid wealth inequality in the data. The distribution of net liquid wealth in the 2016 SCF based on the definition of Kaplan et al. (2014) and Carroll et al. (2017) [49] has a Gini coefficient of 0.89.[50]

The second major discrepancy between the model and the data is that the model substantially underdelivers the fraction of agents who are close to their borrowing constraints. Specifically, the baseline model implies that less than 1% of the population is hand-to-mouth (H2M)—defined as agents whose liquid wealth does not exceed their half-month income—whereas the corresponding share based on net liquid wealth in the SCF is 0.31. The baseline model also significantly underpredicts the H2M shares at virtually all ages compared to what is observed empirically (Figure 5). In SCF, the H2M share starts at around 40% between ages 25 and 45, then gradually falls to below 10%, with a brief increase immediately after retirement. The discrepancy is consistent with the fact that, in this model, strong precautionary saving motives make agents build asset buffers and remain far from their borrowing limits. As a result, even the young agents who start off their working life mostly constrained are able to leave H2M status shortly after.

In addition to wealth moments, we can also compare the model-implied Marginal Propensities to Consume (MPCs) with those elicited in the SCE. This follows the use of survey-based stated MPCs by Christelis et al. (2019) and Fuster et al. (2020). Recognizing that the MPCs from SCE are elicited as the fraction of a hypothetical \$500 windfall to be consumed, I compute the model-based MPCs using the same definition.[51] Because

[49] 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.

[50] I exclude the households in SCF with negative net liquid wealth. The former is meant to be consistent with the no-borrowing constraint assumption.

[51] Unlike the theoretical definition of MPC as the partial derivative of the consumption function with respect to market resource, $\frac{\partial}{\partial m_{i,\tau}} c^*_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau})$, the MPC calculated here, $\frac{c^*_\tau(u_{i,\tau}, m_{i,\tau}+\Delta m, p_{i,\tau}) - c^*_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau})}{\Delta m}$, varies with the size of Δm.

the model generates relatively few H2M households, the average MPC in the stationary distribution is only 0.15, about 10 percentage points below the SCE average of 0.26. Unlike the relatively flat empirical age profile, which remains in the 0.2–0.3 range, the model produces a pronounced U-shaped MPC pattern over the life cycle. The differences of optimal consumption/saving policies and shifts of the asset distribution across ages jointly drive this pattern. On one hand, in standard life-cycle settings, the optimal consumption rule implies that, for a given level of wealth, younger agents have higher MPCs than older ones. On the other hand, young agents in the model are disproportionately concentrated at low wealth levels, which raises their average MPC.

Despite these differences, the baseline model still generates a hump-shaped profile of average wealth over the life cycle, closely matching the net liquid wealth pattern observed in the SCF (Figure 5). Allowing for voluntary bequests in the final period prevents retired agents from fully running down their assets. In Appendix Figure A.9, I also show that the model-implied expected consumption growth follows an intuitive life-cycle pattern, gradually declining from youth and flattening at older ages. Echoing the finding in Table 2, these patterns show that the ex-ante expectations data display patterns that align closely with the model's predictions.

6.2. An alternative model with subjective perceptions of risks

This section presents an alternative model with recalibration of perceived risks, which yields a significant improvement in the model fit to data relative to the baseline. The baseline model maintains the FIRE assumption under the calibrated risks. However, to capture the gap between subjective and objective income risks identified in the previous section, it is necessary to relax this assumption. I modify the baseline model so that the perceived risks determine agents' consumption and savings decisions, while potentially differing from the true underlying risk parameters that govern the actual draw of income shocks, as calibrated in the baseline model. Denote the actual and perceived income risk parameters by $\Gamma = [\sigma_\psi, \sigma_\theta, \mho, \mathbb{E}, \mathbb{G}]$ and $\tilde{\Gamma} = [\tilde{\sigma}_\psi, \tilde{\sigma}_\theta, \tilde{\mho}, \tilde{E}, \tilde{\mathbb{G}}]$, respectively. In various model specifications considered later, a subset of $\tilde{\Gamma}$ may differ from those in Γ. Furthermore, some of the parameters in $\tilde{\Gamma}$ or Γ may take different values across agents.

In any subjective model, it is $\tilde{\Gamma}$ that determines households' expectations of future income dynamics in their consumption/saving problems, as characterized in Equation 15 and value functions in Equation 22. Hence, the optimal consumption/saving $c^*_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau})$ and $a^*_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau})$ differs across agents with different $\tilde{\Gamma}$. In the meantime, the evolution of the asset distribution from age $\tau - 1$ to τ is governed by a new transition function $\tilde{P}$, which is different from the P in the baseline model defined in Equation 24. In contrast to the objective model, $\tilde{P}$ is a joint function of agents' optimal consumption and saving decisions, which are determined by their subjective beliefs about income risk, $\tilde{\Gamma}$, together with the objective income risk process, Γ, that governs the actual realization of income shocks and thus the resulting income distribution.

$$\tilde{\psi}_\tau(\tilde{B}) = \int_{\tilde{x}\in\tilde{X}} \tilde{P}(\tilde{x}, \tau - 1, \tilde{B}) d\tilde{\psi}_{\tau-1} \quad \text{for all} \quad \tilde{B} \in \tilde{B}(X) \tag{25}$$

Separating subjective from actual income processes also conceptually clarifies two distinct channels through which idiosyncratic income risk shapes asset accumulation and inequality. The first is the "choice" channel, which operates *ex-ante* via agents' consumption–saving decisions, driven by their *perceived* income risks. The second is the "outcome" channel, which operates *ex-post* through the *realized* dispersion of income shocks. To the extent that the subjective and actual income processes differ from each other, we can use the two as separate inputs to quantify the contribution of the two channels.

The preferred specification/calibration in this paper is a fully specified subjective model, denoted as *SHPRSUR*, or the "Subjective" model, for short. In this model, the actual wage and unemployment risks are kept almost the same as the baseline and remain homogeneous (a minor adjustment of wage risk due to unobserved heterogeneity). Meanwhile, the level and the heterogeneity in perceived wage and unemployment risks are recalibrated to be consistent with the survey data. The recalibration takes into account all the stylized patterns discussed in the first part of the paper: (a). heterogeneous, and lower average perceived wage risks than the true wage risk, which stems from both unobserved heterogeneity and overconfidence; (b). heterogeneous perceptions of unemployment risks. Below, I describe these incremental recalibrations in detail. The exact values of parameters are reported in Table 4 in addition to other alternative specifications considered later on.

Lower perceived wage risks. The recalibration of perceived wage risks to a lower level requires adjustments consistent with the underlying sources of the wedge: the exact degree of unobserved heterogeneity and overconfidence identified in the previous section. I discipline the sizes of the two using the estimates of σ_ξ and δ. In particular, subjective values $\tilde{\sigma}_\psi$ and $\tilde{\sigma}_\theta$ are both set to be 0.03 as the perceived wage risks, which exactly add up to the total PR in SCE of 3 percentage points.[52] Their objective values σ_ψ and σ_θ are 0.147, as the true wage risks. Meanwhile, the perceived life-cycle growth profiles $\tilde{\mathbb{G}}$ are heterogeneous with a dispersion equal to the size of $\sigma_{\xi,\psi} = 0.028$. To be consistent with the previous identification results that the expectational dispersion fully reflects the unobserved heterogeneity, the actual growth profiles $\mathbb{G}$ are also assumed to be exactly the same as perceptions. All modifications combined, this corresponds to the *SLPR* calibration in Table 4.

It is worth further clarifying the link between the unobserved heterogeneity σ_ξ and the recalibrated dispersed growth profiles $\mathbb{G}$. Note that crucially, only the heterogeneity contained in the permanent component of the σ_ξ, namely $\sigma_{\xi,\psi}$ is used for calibrating heterogeneous growth profiles. I assume a half of the 4-percentage point heterogeneity identified in Section 4.4.1 reflects the permanent difference in wage growth rates, that is $\sigma_{\xi,\psi} = \sqrt{0.04^2/2} = 0.028$.[53] I assign each agent to one of three equally likely deterministic wage growth profiles, designed to match an annual standard deviation of the same size.[54]Figure A.8 visualizes these profiles, with the mean trajectory corresponding to the baseline calibration $\mathbb{G} = \{G_\tau\}_{\tau=1,\dots,L}$.

Heterogeneous perceived wage risks. The second recalibration is more straightforward: agents perceive heterogeneous wage risks, corresponding to the *SHPR* specifica-

[52]In the Appendix A.4, I show that under alternative ratios of permanent and transitory component $\kappa = \frac{\tilde{\sigma}_\psi}{\tilde{\sigma}_\theta}$, the subjective model remains a significant improvement relative to the baseline.

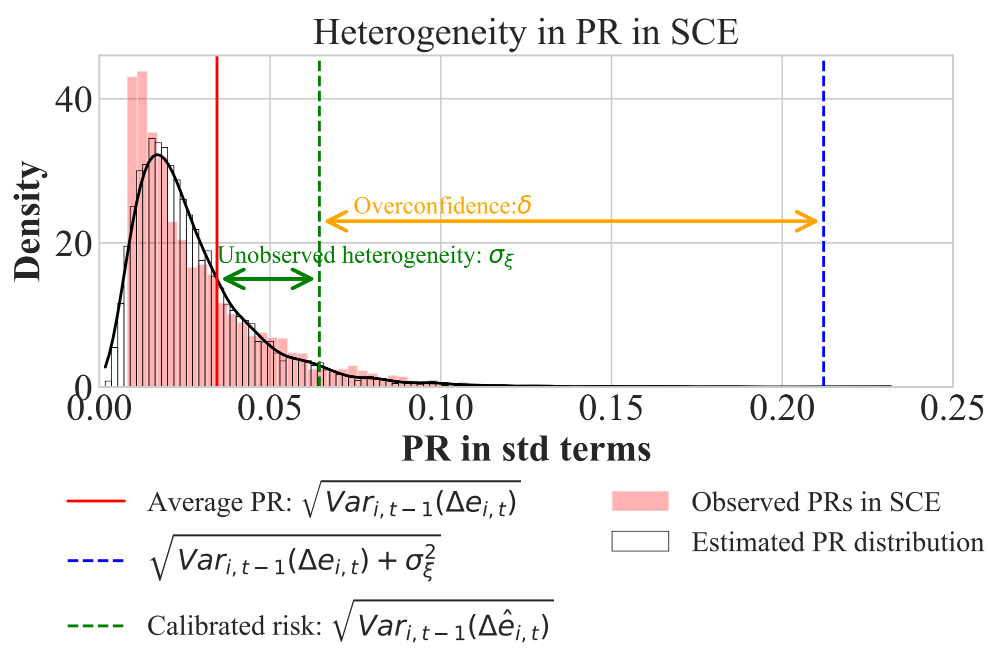
[53]I abstract from the heterogeneity in transitory component ($\tilde{\sigma}_\theta = 0.028$), as its effects largely average out over the life cycle. This simplification likely understates unobserved heterogeneity, making the resulting calibration a conservative lower bound.

[54]With the wage growth expectations across agents approximately following a normal distribution with mean μ and variance σ^2, the three equally probable growth rates can be approximated by $\mu - \sqrt{3/2}\sigma$, μ, and $\mu + \sqrt{3/2}\sigma$, respectively.

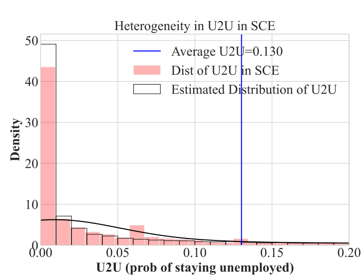
tion reported in Table 4. This means that $\tilde{\sigma}_\psi$ and $\tilde{\sigma}_\theta$ take different values across agents. I directly calibrate the heterogeneity in PRs by fitting a truncated log-normal distribution to the cross-sectional distribution of the time-average PRs in the SCE, as shown in Figure 4A. The estimated distribution is then discretized into equally probable values used in the model, i,e., $\{0.01, 0.02, 0.04\}$ for both $\tilde{\sigma}_\psi$ and $\tilde{\sigma}_\theta$. The figure also visually illustrates the difference between the average perceived risk and calibrated risk stemming from the combination of unobserved heterogeneity σ_ψ and overconfidence δ, both of which are separately identified.

FIGURE 4. Calibration of heterogeneous perceived risks in the SCE

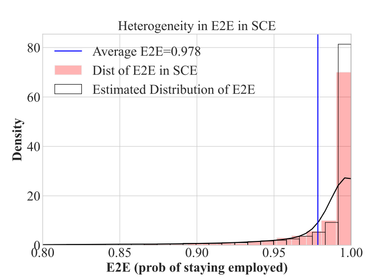
A. Perceived wage risk



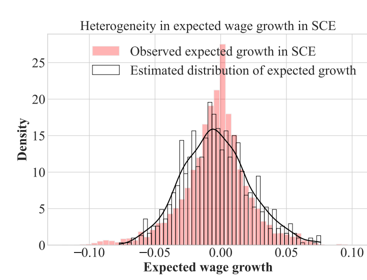
B. U2U



C. E2E



D. Expected wage growth



Note: The top figure plots the observed distribution of the perceived income risks from the SCE and the fitted truncated log-normal distribution. The exact procedure of identifying σ_ξ and δ is discussed in Section 4.4.1. The other three figures plot the distribution of unemployment risks and expected wage growth in the survey, as well as their fitted distribution.

Heterogeneous perceived unemployment risks. Third, in addition to subjective wage risks, agents also perceive heterogeneous unemployment risks, meaning that $\tilde{E}$ and $\tilde{U}$ differ across agents. This attains the full specified subjective model *SHPRSUR* in Table 4. The heterogeneity in the perceived unemployment risk is calibrated similarly by fitting a truncated log-normal distribution to the cross-section of perceived *U2U* and *E2E* probabilities (as shown in Figure 4). [55] The estimated distribution is further discretized

[55] Informed by the observed low correlation at the individual level between perceived wage risks, job separation, and finding probabilities in SCE, I estimate the distribution of U2U and E2E independently

TABLE 4. Model Parameters: Perceived vs. Actual

	Perceived					Actual				
Model	σ_ψ	σ_θ	E	$\mho$	$\mathbb{G}$	$\tilde{\sigma}_\psi$	$\tilde{\sigma}_\theta$	$\tilde{E}$	$\tilde{\mho}$	$\tilde{\mathbb{G}}$
Baseline	0.15	0.15	0.96	0.18	Fig. A.7A	0.15	0.15	0.96	0.18	Fig. A.7A
SLPR	0.03	0.03	0.96	0.18	Fig. A.7B	0.147	0.147	0.96	0.18	Fig. A.7B
SHPR	{ 0.01, 0.02 0.04 }	{ 0.01, 0.02 0.04}	0.96	0.18	Fig. A.7B	0.147	0.147	0.96	0.18	Fig. A.7B
SHUR	0.15	0.15	{ 0.96, 0.998, 1.0 }	{ 0.0, 0.064 0.199}	Fig. A.7B	0.147	0.147	0.96	0.18	Fig. A.7B
Subjective (SHPRSUR)	{ 0.01, 0.02 0.04}	{ 0.01, 0.02 0.04}	{ 0.96, 0.998, 1.0 }	{ 0.0, 0.064 0.199}	Fig. A.7B	0.147	0.147	0.96	0.18	Fig. A.7B
SHPRUR	{ 0.01, 0.02 0.04}	{ 0.01, 0.02 0.04}	{ 0.96, 0.998, 1.0}	{0.0, 0.064 0.199}	Fig. A.7B	0.147	0.147	{0.96, 0.998, 1.0 }	{0.0, 0.064 0.199}	Fig. A.7B
HPRSUR	{ 0.01, 0.02 0.04}	{ 0.01, 0.02 0.04}	{ 0.96, 0.998, 1.0}	{0.0, 0.064 0.199}	Fig. A.7B	{ 0.01, 0.02 0.04}	{ 0.01, 0.02 0.04}	0.96	0.18	Fig. A.7B
HPRUR	{ 0.01, 0.02 0.04 }	{ 0.01, 0.02 0.04}	{0.96, 0.998, 1.0 }	{0.0, 0.064 0.199}	Fig. A.7B	{ 0.01, 0.02 0.04}	{ 0.01, 0.02 0.04 }	{0.96, 0.998, 1.0}	{0.0, 0.064 0.199}	Fig. A.7B
Biased Exp.	{ 0.01, 0.02 0.04}	{ 0.01, 0.02 0.04}	{0.96, 0.998, 1.0}	{0.0, 0.064 0.199}	Fig. A.7B	0.147	0.147	0.96	0.18	Fig. A.8 (d)
Fanning	{ 0.01, 0.02 0.04}	{ 0.01, 0.02 0.04 }	{0.96, 0.998, 1.0}	{0.0, 0.064 0.199 }	Fig. A.8 (a)	0.147	0.147	0.96	0.18	Fig. A.7B
Hump	{ 0.01, 0.02 0.04}	{ 0.01, 0.02 0.04}	0.96	0.18	Fig. A.8 (b)	0.147	0.147	0.96	0.18	Fig. A.7B
Right skew	{ 0.01, 0.02 0.04}	{ 0.01, 0.02 0.04}	{0.96, 0.998, 1.0}	{0.0, 0.064 0.199 }	Fig. A.8 (c)	0.147	0.147	0.96	0.18	Fig. A.7B

Note: The table shows all parameterizations under different model assumptions. Heterogeneity in any parameter is directly expressed as equally probable values, discretized from its estimated underlying distribution.

into three equally probable grid points [0, 0.02, 0.24] for $U2U$ and [0.96, 0.99, 1.0] for $E2E$. 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.[56]

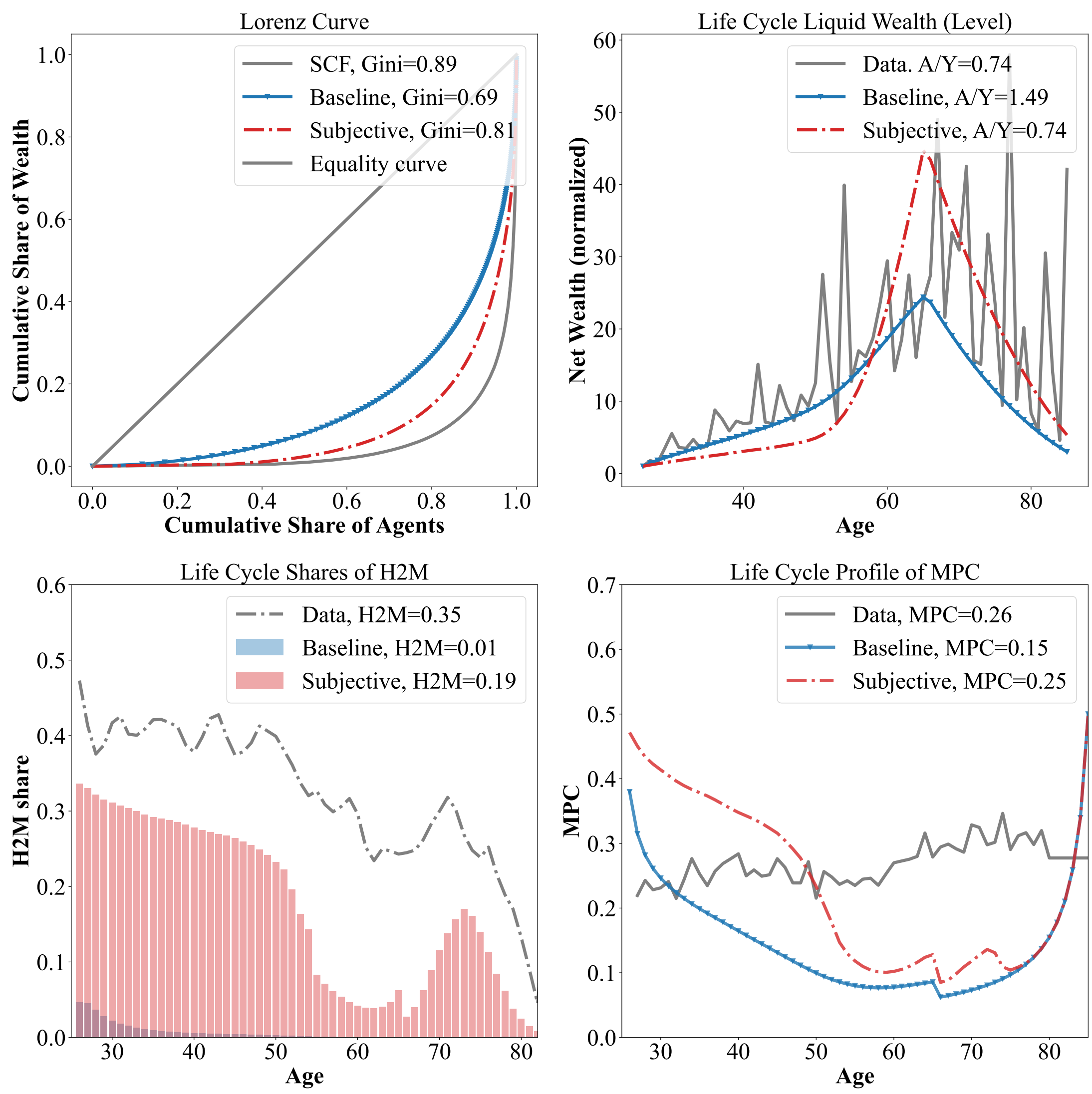
Results from the subjective model. The recalibrated model, by incorporating subjective perceptions of risk, markedly enhances its fit to the data across a range of moments. Figure 5 displays key moments of the stationary distribution generated by the subjective model alongside those of the baseline. The subjective model pushes the Lorenz curve

from that of the wage risks. The correlation between perceived risks and U2U and E2E probabilities is 0.07, and -0.1, respectively; the correlation between job separation and job finding expectations is 0.01.

[56]See Ahn and Hamilton (2020), Gregory et al. (2025), and Castro et al. (2025) for evidence on ex-ante heterogeneity in job transitions; Savoia (2023) and Oh and Rogantini Picco (2025) for the macroeconomic consequences of such heterogeneity.

further outward, yielding an 11–percentage point rise in the Gini coefficient—from 0.70 in the baseline to 0.81. In the subjective model, the share of hand-to-mouth (H2M) agents is 19%, which is 18 percentage points higher than in the baseline, indicating that a large portion of households are close to liquidity constraints, of a similar magnitude to that in the objective model. A particularly striking feature is that the subjective model produces a life-cycle pattern of H2M incidence that closely mirrors the empirical data. As a result, the model-implied aggregate MPC increases from 0.15 to 0.25, driven mainly by higher MPCs among young and middle-aged households. The model still delivers a gradual decline in MPCs over the life cycle as assets are accumulated, in contrast with the nearly flat MPC profile from youth through old age.[57]

FIGURE 5. Key model moments: baseline versus subjective



Note: The figure displays model-implied moments alongside their empirical counterparts, for both the baseline and the subjective model (*SHPRSUR*). Shown are: the Lorenz curve of household wealth (upper left); life-cycle profiles of average wealth normalized by its value at age 25 (upper right); reported marginal propensities to consume (MPCs) out of a hypothetical $500 windfall (bottom left); and the share of H2M households over the life cycle (bottom right). All wealth statistics are based on net liquid wealth from 2016 SCF, and reported MPCs are obtained from SCE.

[57] Matching the life-cycle pattern of MPCs is beyond the ambition of this paper. A stable and flat MPC profile over life is likely due to reasons unrelated to expectations and observed demographic variables, instead due to the presence of substantial, latent heterogeneity, as shown by Lewis et al. (2024); Kosar and Melcangi (2025).

6.3. An anatomy of the subjective model

This section breaks down the improvement of the subjective model relative to the baseline into different mechanisms.

Wage risks versus unemployment risks. The recalibration of wage risks and heterogeneous perceived unemployment risks contributes to the increased model fit, but to varying degrees. These correspond to the *SLPR, SHPR,* and *SHPUR* specifications in Table 4. The "Subjective lower wage risk", "Subjective wage risks", and "Subjective unemployment risk" in Table 5 show the model moments from each of these specifications.

First, both wage and unemployment risk recalibration are equally important to accounting for the liquid wealth inequality. Either adjustment alone increases the Gini coefficient by about 7 percentage points. The combined effects are an 11 percentage-point increase from the baseline to the subjective model, but incorporating heterogeneity in wage risks partially offsets this increase. Both channels effectively induce more heterogeneous consumption policies and, as a result, greater wealth inequality. Second, it is primarily the recalibration of unemployment risk that raises the share of H2M agents. Recalibrating perceived unemployment risks alone to the baseline model increases the H2M share from 1% to 12%. Although both forces widen the wealth distribution, the unemployment risk heterogeneity particularly leads to an extension of the borrowing-constrained agents at the left end of the distribution.

At the same time, wage and unemployment risk recalibration contribute roughly equally to a total 10-point increase in the average MPC. While the model-implied MPCs are tightly linked to the wealth distribution, perceived risks also directly shape ex-ante decisions conditional on wealth. Therefore, a higher model-implied MPC does not entirely channel through a better prediction of wealth distribution. This suggests that recalibrating both wage and unemployment risks is crucial for improving the model's predictions of MPCs.

Choice versus outcome. We can also examine whether the subjective model's better fit to data patterns comes from the "choice" or the "outcome" channel, or exactly from the wedge between perceived risks and actual income risks. I find that the "choice" channel is the key. To put it differently, what matters is the recalibration of perceived risks according to the survey, no matter if such perceptions are also the actual income processes. In the three variants of the subjective model, where either the actual unemployment risks or wage risks are assumed to be the same as perceptions, wealth Gini, the H2M share, and average MPCs are rather similar to the subjective model. In the first version,, the actual $E = \tilde{E}$ and $\mho = \tilde{\mho}$, taking subjective heterogeneous values. In the second model $\sigma_\psi = \tilde{\sigma}_\psi$, $\sigma_\theta = \tilde{\sigma}_\theta$, both are taking subjective values. In the third version, both actual wage risks and unemployment risks align with perceptions. Their statistics are reported under *SHPRUR*, *HPRSUR*, and *HPRUR* in Table 5.

Overconfidence versus heterogeneity. Our full subjective model incorporates both ex-ante heterogeneity in life-cycle growth rate and overconfidence in that perceived wage risks are significantly lower than the true risks. It is interesting to ask which of the two channels contributes to the improved model fit. By shutting down the overconfidence channel in the subjective model, namely setting σ_ψ and σ_θ to be exactly as those perceived, it effectively captures the impacts of only having heterogeneity in wage growth rates. The gap between Subjective and HPRSUR in the Table 5 reflects the sole impact of overconfidence. It turns out that the heterogeneity is more consequential than overconfidence in terms of increasing the model-implied inequality and H2M shares.

To summarize, the subjective model highlights the central finding of this paper: even though the perceived income risks reported in surveys may not perfectly correspond to the objective processes that govern stochastic income shocks, households make savings decisions based on these perceptions. As a result, once the perceptions are recalibrated to reflect the level and heterogeneity in the survey, the model generates predictions about wealth accumulation that are more consistent with the empirical data. Further breakdown suggests that, within this improvement in model predictions, incorporating realistic heterogeneity in perceived risks is particularly important. The following sections assess the additional robustness of this claim across alternative specifications and assumptions.

TABLE 5. Summary of model results and data

Model/Data	Gini	Bottom 0.9	Bottom 0.7	Bottom 0.5	Average A/Y	H2M share	Average MPC
Data	0.89	0.15	0.04	0.01	0.74	0.35	0.26
Baseline	0.70	0.41	0.18	0.08	1.50	0.01	0.15
Sub.Lower Wage Risk	0.77	0.32	0.12	0.05	1.24	0.02	0.18
Sub. Wage Risk	0.72	0.40	0.16	0.07	1.16	0.02	0.18
Sub. UE risk	0.77	0.33	0.12	0.04	1.09	0.12	0.20
Subjective	0.81	0.29	0.08	0.02	0.75	0.19	0.25
SHPRUR	0.81	0.29	0.08	0.03	0.81	0.17	0.23
HPRSUR	0.79	0.33	0.09	0.03	0.68	0.21	0.26
HPRUR	0.79	0.33	0.09	0.03	0.74	0.19	0.24
Biased Expectation	0.76	0.36	0.12	0.04	0.68	0.18	0.25
Fanning	0.80	0.30	0.09	0.03	0.74	0.18	0.25
Hump	0.81	0.29	0.08	0.02	0.80	0.18	0.24
Right Skew	0.81	0.30	0.09	0.03	0.81	0.18	0.24
CRRA	0.85	0.23	0.05	0.01	0.97	0.23	0.28
Patience	0.83	0.26	0.06	0.02	0.89	0.21	0.26
Bequests	0.82	0.28	0.07	0.02	0.78	0.22	0.26
Borrowing	0.86	0.24	0.04	-0.01	0.67	0.31	0.25

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, the shares of hands-to-mouth agents (H2M), and average MPC in the partial-equilibrium stationary distribution under various model specifications. H2M is defined as those whose liquid wealth is no more than two weeks' (1/24 of annual) income. MPC is calculated in the model as the proportion of a hypothetical one-time $500 windfall spent, as measured in the SCE. Other wealth statistics in the data are computed for both net liquid wealth in the 2016 SCF.

6.4. Additional Considerations

6.4.1. Biases in expectations

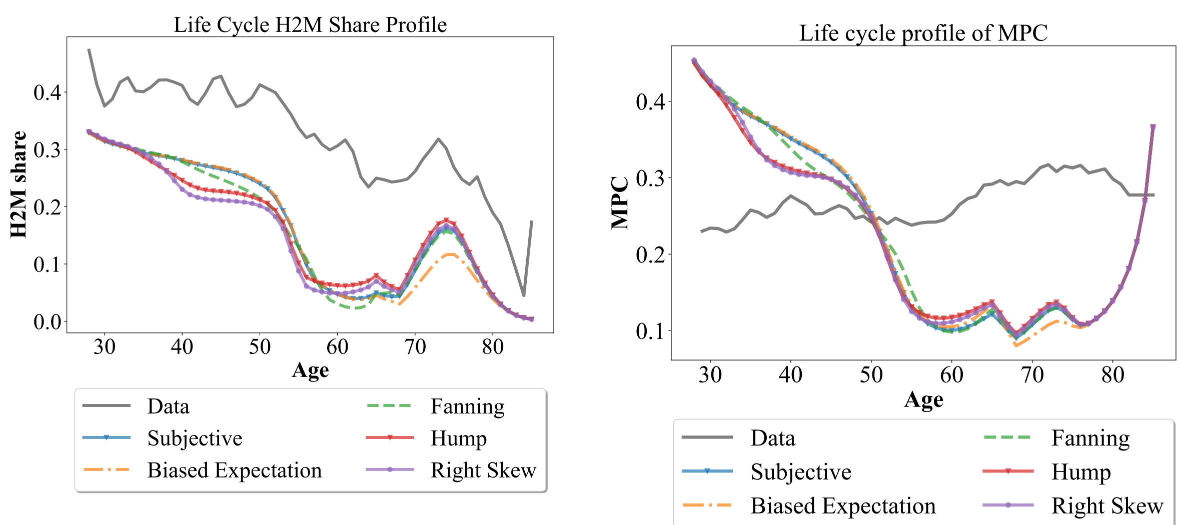
In this section, we consider the importance of biases in the expected growth rate. Recall in Section 4.4.1, I caution that the expectational dispersion across agents may not fully reflect unobserved heterogeneity σ_ξ; rather, it is due to expectational biases $\epsilon_{i,t}$. This essentially implies that the agents subjectively view their life cycle profiles as more distinct than the true heterogeneity.[58] Since we cannot directly identify the size of the biases, but infer their upper bound, we consider this as robustness instead of our preferred specification. In particular, we recalibrate the subjective model by letting subjective life-cycle profiles $\tilde{\mathbb{G}}$ be different from the objective ones. We assume that only half of the observed dispersion in expected wage growth rates in $\sigma_\xi = 0.04$ is due

[58] One mechanism through which such patterns emerge might be the "overpersistence" bias as argued by Rozsypal and Schlafmann (2023). If agents systematically overly perceive their transitory shocks to be more persistent, there will be biases in income expectations leading to a wider expectational dispersion than the actual income realizations.

to true unobserved heterogeneity, whereas the other half stems from idiosyncratic biases in their respective expectations. This effectively makes $\sigma_{\xi,\psi}$, the dispersion in permanent growth rate, half of the previous calibration at the value of 0.015. The exact parameterization is reported in Table 4. Under this assumption, agents expect more dispersion in growth rates than the actual heterogeneity. The dispersion of the true life cycle growth profiles shrinks, as shown in Figure A.8.

Figure 6 plots the results under such assumptions in addition to the preferred specification. This alternation yields a lower Gini of liquid wealth than the preferred model, which is nevertheless still 10 percentage points higher than the baseline. This is because limiting the true heterogeneity in life cycle wage growth profiles also limits the ultimate income inequality. However, the fraction of H2M only shrinks slightly from 19% to 18%, which is still substantially larger than the baseline's prediction. The model-implied MPCs remain at 0.25, as the subjective model. Taking this evidence together, the model's improved fit to data is robust to the existence of expectational biases in wage growth rate expectations.

FIGURE 6. Key model moments from the subjective model: other considerations



Note: The upper panel shows, under various alternative 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). The SCF profile is plotted as the six-year moving average.

6.4.2. Unfolding of expectational heterogeneity over the life cycle

With heterogeneous life-cycle profiles of wage growth rates, which are partially or fully expected by the agents, we assume that the agents perceive that the degree of permanent heterogeneity in growth rate per year over the life cycle stays the same. This implies that the heterogeneity in the level of the wage accumulates at a constant pace over the life before retirement. Due to a lack of data on the entire life-cycle expectations of wage rates, this comes as a natural assumption for our baseline. However, it may also be plausible to assume that the predictable heterogeneity across agents differs over the stages of working life. It is also possible that such heterogeneity does not fully reflect in agents' expectations early on and gradually does so. [59]

[59] Guvenen (2007), for instance, models the implications of agents gradually learning about their ex-ante heterogeneous growth rates of life cycle income.

Assuming the actual deterministic profiles $\mathbb{G}$ stay the same as in the subjective model, I consider three alternative subjective unfolding patterns of life-cycle wage heterogeneity. All profiles share the same average yearly heterogeneity in wage growth rate of a 2.8 percentage points as $\sigma_{\xi,\psi}$, but differ in their relative shapes over the life cycle. The first is a "fanning-out" profile in that the perceived heterogeneity in growth rates monotonically increases over the life. With life unfolding, agents increasingly become dispersed in their expected wage growth rates. The second is in a hump shape, in that the heterogeneity widens in the middle of working life, then shrinks later. The third corresponds to having a right-skewed unfolding shape in that the heterogeneity starts from the highest level and gradually dissipates over the life. This dynamic may have to do with learning over life, over which agents gradually accumulate observations for them to correctly infer their true permanent income.

The results under these variants of the preferred model are plotted in Figure 6 and reported in Table 5. In terms of asset Gini, H2M share, and MPC, different models yield almost identical results. The major differences between these models lie in their steady-state level of the liquid wealth to income ratio. With either a hump-shaped or right-skewed profile, the wealth-to-income ratio is slightly higher than in the other cases. All in all, the takeaway is that the subjective model's overall improvement is also robust to different unfolding patterns of life-cycle heterogeneity, as long as such heterogeneity is already incorporated.

6.4.3. Calibration via indirect inference

Our baseline calibration, as well as the recalibration, externally fixes the preference parameters of the model. The purpose there is to show the improvement in model fit due to calibrating perceived income risks without altering preference parameters. In this section, I pursue an alternative strategy, which has been the convention of the existing literature. That is that the preference parameters are internally calibrated to match observed moments. The purpose here is to show that incorporating subjective perceptions of income risks also improves the model's fit across different moments.

For both the baseline model and the preferred subjective model, I consider separately targeting the following seven data moments that are often of interest the literature. The first four are life cycle profiles of (a) liquid wealth, (b) H2M shares, (c) MPCs and (d) the expected consumption growth factors $\tilde{\mathbb{E}}_{i,\tau}(\frac{c_{i,\tau+1}}{c_{i,\tau}})$. In addition to targeting life cycle profiles, I also target three population average moments directly, which are average (e) H2M ratio, (f) MPC, and (g) average liquid wealth to income ratio. The expected consumption growth profile is from SCE.

Among these calibration strategies based on different targeted moments, what is particularly novel is the one that targets the *expected* consumption growth, rather than actual spending or wealth profiles. The latter reflects indirect inference based on ex-post outcomes, whereas the ex-ante approach is based on matching directly with the model's behavioral predictions. In particular, heterogeneous-agent models imply that intertemporal choices under uninsured risks generate a systematic relationship between individuals' expectations of future income, perceived risk, and expected consumption growth as dictated by the Euler equation, as shown in Section 4.6. Such a relationship depends on the agent's preference parameters β and ρ. My calibration builds on recent studies that estimate preference parameters using ex-ante survey expectations.[60]

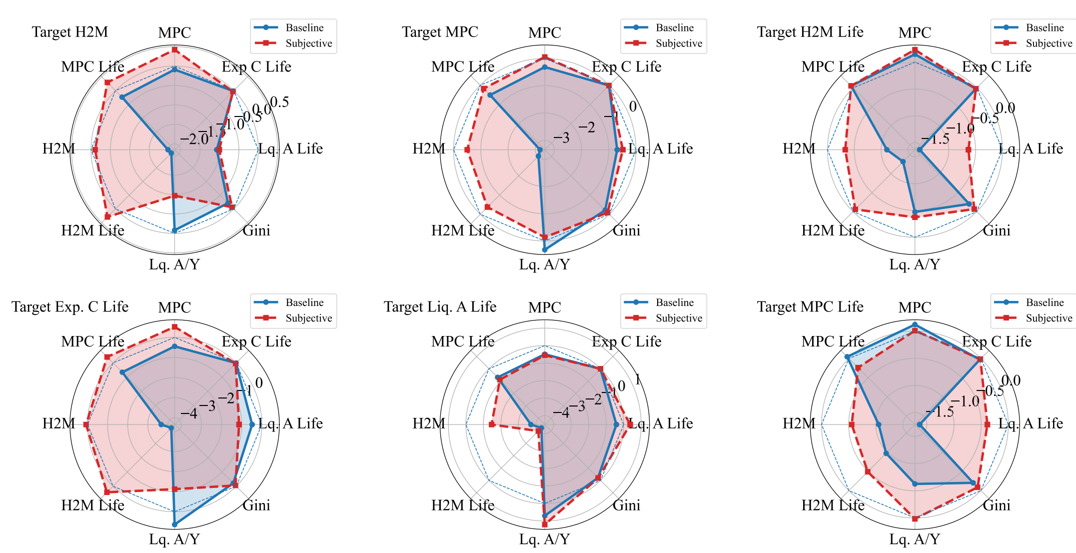
[60] For example, Crump et al. (2022); Dräger and Nghiem (2021); Christelis et al. (2020) estimate Euler

Moreover, conditioning directly on subjective income expectations allows identification of preference parameters that are otherwise unobservable—echoing Manski (2004)'s insight that expectation data enables inference without imposing indirect assumptions about beliefs.

Figure 7 compares the cross-moment fit of the baseline and the preferred subjective model when they are calibrated using indirectly inferred values of β and ρ for matching different target moments. The difference between the model-implied moment and its data counterpart is all expressed in log deviations. Therefore, an octagon that spreads to coordinates of zero across all data moments indicates a perfect fit of the model to the data.

Regardless of which target moment is selected, the clearest pattern in Figure 7 is that the subjective model generally delivers a closer fit across moments than the baseline model. Both models share a common trade-off between matching wealth-to-income ratios and producing realistic H2M shares and MPCs. Parameterizations that generate more realistic average liquid wealth levels typically imply H2M shares and MPCs that are too low relative to the data. Conversely, specifications that better match H2M shares and MPCs tend to understate the extent of wealth accumulation in the economy. This trade-off is substantially weaker in the subjective model. Intuitively, this improvement arises because separating subjective and heterogeneous beliefs from actual income realizations relaxes the tight linkage between the wealth distribution and MPCs.

FIGURE 7. Model fit across moments: baseline versus subjective model



Note: This figure shows the model fit in terms of eight population or life cycle moments based on an indirectly calibrated discount factor β and the CRRA coefficient ρ by targeting a certain data moment. All data-model difference is expressed in log deviations.

6.4.4. Heterogeneous/non-homothetic preference and borrowing constraint

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.[61] Despite such indirect evidence, however, the

equations with ex-ante data to infer the intertemporal elasticity of substitution and prudence.

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

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.

Also, the literature has increasingly relied on nonhomothetic preferences, rather than unconditional heterogeneity, to achieve the same goal, as emphasized by Dynan et al. (2004); Straub (2019). The key mechanism is that the non-homotheticity makes saving a luxury good: as permanent income increases, one's "joy for saving" increases. This leads to a marginal propensity to consume out of permanent income that falls below one. This contrasts with the class of homothetic models considered in this paper.

Rather than microfounding such preferences, I adopt a reduced-form approach by recalibrating ex-ante preference parameter heterogeneity to replicate similar qualitative patterns. Specifically, I study three extensions of the subjective model in which agents with steeper life-cycle income growth are also endowed with preference parameters that imply systematically higher saving rates. These agents receive a higher discount factor β, a lower coefficient of relative risk aversion ρ[62], and a stronger bequest motive near the end of life. All other income processes and calibrations remain identical to those in the baseline subjective model. From low to high growth types, their respective values are $\rho = \{1.1, 2.0, 3.0\}$; $\beta = \{0.95, 0.97, 0.99\}$; $\phi = \{0.02, 2.0, 5.0\}$. The three models' results are reported in Table 5, under the names of *CRRA*, *Patience*, and *Bequests*.

The income-dependent preference heterogeneity further widens the wealth distribution relative to the subjective model, particularly by increasing the savings of the wealthy in the model. All three models increase the wealth Gini by 4, 2, and 1 points, respectively. The H2M share also increases by 4, 2, and 3 percentage points, respectively, and the average MPC changes from 0.25 to 0.28, 0.26, and 0.26, respectively. Meanwhile, some of the models yield a higher average wealth-to-income ratio from 0.75, to 0.97, 0.89, and 0.78. Consistent with the literature, the introduction of non-homothetic preferences has the merit of generating wealthier households in the model while maintaining a good fit of the lower end of the distribution. Since this paper emphasizes the role of ex-ante heterogeneity in permanent income profiles across agents, incorporating non-homothetic preferences serves as a natural complementary feature to improve the model fit.

Lastly, it is also natural to introduce another realistic feature that turns out to be complementary to our subjective model. In particular, we relax the zero-borrowing constraint in Equation 16 so that the agents in our model can actually borrow up to their "natural borrowing constraint". What is interesting in this alternative environment is the fact that the natural borrowing constraint is actually dependent on the perceived unemployment risks. Unsurprisingly, as reported in the "Borrowing" model in Table 5, the wealth distribution has a leftward shift, which increases the wealth Gini by 5 percentage points, the share of H2M by a substantial 12 percentage points, and yields a rather similar average MPC of 0.25.

Taken together, these extensions show that adjusting subjective and heterogeneous income risks is not only consistent with, but in fact reinforces, the additional model ingredients typically employed in the literature to improve the empirical fit of the standard heterogeneous-agent life-cycle model. That said, even though our subjective

[62] On one hand, a smaller ρ reduces the precautionary saving motives. However, it increases intertemporal substitution by reducing present consumption relative to future consumption. The second effect seems to dominate in the aggregate.

model substantially better replicates the empirical patterns, a considerable discrepancy remains, one that the extra features are still required to address. At the same time, it is arguably natural that, once the observed dispersion in income expectations and risk perceptions is explicitly taken into account, the degree of preference heterogeneity needed to fully "bridge the gap" is correspondingly reduced.

6.5. Final discussions

Before concluding, I briefly discuss several other issues related to the robustness of the key insight of this paper and some future research directions.

The focus on wage and unemployment risks. Although this paper focuses on the perception patterns related to two specific sources of labor income risks—wage changes and unemployment transitions—the central conclusion likely extends to total earnings and household dynamics more broadly. Since it is a common practice in the incomplete market macroeconomic models to assume inelastic labor supply, this paper implicitly takes a broad interpretation of the wage risks as on-the-job earning risks. Subjective earning risks, when measured broadly, exhibit patterns in line with those reported in this paper. For example, Caplin et al. (2023) demonstrates that the holistic subjective earning distribution, constructed from separately elicited job-transition probabilities and conditional earnings distributions, displays the same qualitative pattern as in this study: perceived risks are highly heterogeneous between individuals and are lower than the dispersion of actual income changes.

A more general treatment of the heterogeneity in perceived income processes. This paper's treatment of heterogeneity in subjective income processes is limited to the heterogeneity in a small set of parameters for a commonly adopted income process. In the Appendix Figure A.3, I adopt a machine learning approach to cluster the subjective distribution patterns into 10 groups. The cluttered distributions are widely heterogeneous. But across all types, the dispersion of the subjective distribution remains at a lower range of values than the calibrated risks, consistent with my main finding. It would certainly be fruitful in future research to incorporate richer heterogeneity in perception patterns using non-parametric methods into the heterogeneous-agent model considered in the paper.

Non-Gaussian income processes. A large body of work—much of which uses administrative income records(Guvenen et al. 2021)—shows that labor earning dynamics are not well captured by the standard Gaussian process. It is worth clarifying that the results in this paper on the discrepancy between perceived and calibrated risks are unlikely to be sensitive to considering non-Gaussian income processes for the following two reasons.

Most importantly, the literature typically shows that deviations from Gaussian dynamics largely arise from discrete job transitions that are embedded in observed earnings changes. In this respect, this paper's analysis explicitly incorporates such risks through separately calibrated job transition probabilities. Second, although a richer specification of the stochastic process is proven to characterize earning dynamics better, it does not rule out the possibility that income risks are perceived differently by the agents for the reasons discussed in this paper. With that said, it would be a fruitful direction of research to combine the subjective earning distributions with high-quality income records to uncover richer earning/income dynamics.[63]

[63] A recent example of this work is Arellano et al. (2024).

General-equilibrium. The core insights of this paper are already well captured by the partial-equilibrium life-cycle framework. It is, however, natural to ask whether the quantitative results obtained so far continue to hold in a setting where the real interest rate is determined endogenously through market-clearing in asset markets. In Appendix A.10, I therefore analyze a one-asset general-equilibrium overlapping-generations model in the spirit of Huggett (1996); Carroll et al. (2017); Krueger et al. (2016), in which household savings serve as productive capital. The main conclusion is that, in general equilibrium, all central results of the paper continue to hold despite slight attenuation. I leave it for future research to explore richer implications of perceived income risks once additional important features such as portfolio choices between risky/illiquid assets are introduced, as in Kaplan et al. (2014).

7. Conclusion

A large class of incomplete-market macroeconomic models that features uninsured idiosyncratic income risks and the resulting wealth inequality does not incorporate the observable heterogeneity in income risks as agents perceive. 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, stemming from a higher degree of anticipated heterogeneity and a substantial degree of overconfidence. This 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 using survey data in calibrating heterogeneous-agent models where realistic heterogeneity in expectations/perceptions yields better model predictions. 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 helps economists do a better job of matching empirical patterns within the macroeconomy.

References

Abowd, J. M. and Card, D. (1989). On the covariance structure of earnings and hours changes. *Econometrica: Journal of the Econometric Society*, pages 411–445.

Acharya, S. and Dogra, K. (2020). Understanding hank: Insights from a prank. *Econometrica*, 88(3):1113–1158.

Ahn, H. J. and Hamilton, J. D. (2020). Heterogeneity and unemployment dynamics. *Journal of Business & Economic Statistics*, 38(3):554–569.

Aiyagari, S. R. (1994). Uninsured idiosyncratic risk and aggregate saving. *The Quarterly Journal of Economics*, 109(3):659–684.

Arellano, M., Attanasio, O., Crossman, S., and Sancibrián, V. (2024). Estimating flexible income processes from subjective expectations data: evidence from india and colombia. Technical report, National Bureau of Economic Research.

Arellano, M., Blundell, R., and Bonhomme, S. (2017). Earnings and consumption dynamics: a nonlinear panel data framework. *Econometrica*, 85(3):693–734.

Armantier, O., Topa, G., Van der Klaauw, W., and Zafar, B. (2017). An overview of the Survey of Consumer Expectations. *Economic Policy Review*, (23-2):51–72.

Auclert, A. (2019). Monetary policy and the redistribution channel. *American Economic Review*, 109(6):2333–67.

Bachmann, R., Berg, T. O., and Sims, E. R. (2015). Inflation expectations and readiness to spend: Cross-sectional evidence. *American Economic Journal: Economic Policy*, 7(1):1–35.

Balleer, A., Duernecker, G., Forstner, S., and Goensch, J. (2021). The effects of biased labor market expectations on consumption, wealth inequality, and welfare.

Bayer, C., Lütticke, R., Pham-Dao, L., and Tjaden, V. (2019). Precautionary savings, illiquid assets, and the aggregate consequences of shocks to household income risk. *Econometrica*, 87(1):255–290.

Bloom, N., Guvenen, F., Pistaferri, L., Sabelhaus, J., Salgado, S., and Song, J. (2018). The great micro moderation. Working paper.

Blundell, R., Pistaferri, L., and Preston, I. (2008). Consumption Inequality and Partial Insurance. *American Economic Review*, 98(5):1887–1921.

Broer, T., Kohlhas, A., Mitman, K., and Schlafmann, K. (2021). Information and wealth heterogeneity in the macroeconomy.

Bunn, P., Le Roux, J., Reinold, K., and Surico, P. (2018). The consumption response to positive and negative income shocks. *Journal of Monetary Economics*, 96:1–15.

Cagetti, M. (2003). Wealth accumulation over the life cycle and precautionary savings. *Journal of Business & Economic Statistics*, 21(3):339–353.

Callegaro, M. (2008). Seam effects in longitudinal surveys. *Journal of Official Statistics*, 24(3):387.

Caplin, A., Gregory, V., Lee, E., Leth-Petersen, S., and Sæverud, J. (2023). Subjective earnings risk. Technical report, National Bureau of Economic Research.

Carroll, C., Slacalek, J., Tokuoka, K., and White, M. N. (2017). The distribution of wealth and the marginal propensity to consume. *Quantitative Economics*, 8(3):977–1020.

Carroll, C. D. (2001). Death to the log-linearized consumption euler equation!(and very poor health to the second-order approximation). *The BE Journal of Macroeconomics*, 1(1).

Carroll, C. D. (2006). The method of endogenous gridpoints for solving dynamic stochastic optimization problems. *Economics letters*, 91(3):312–320.

Carroll, C. D., Crawley, E., Slacalek, J., Tokuoka, K., and White, M. N. (2018). Sticky expectations and consumption dynamics. Technical report, National Bureau of Economic Research.

Carroll, C. D. and Kimball, M. S. (2001). Liquidity constraints and precautionary saving. Technical report, National Bureau of Economic Research.

Carroll, C. D. and Samwick, A. A. (1997). The nature of precautionary wealth. *Journal of monetary Economics*, 40(1):41–71.

Castro, R., Lange, F., and Poschke, M. (2025). Labor force transitions. *Handbook of Labor Economics*, 6:819–881.

Challe, E. and Ragot, X. (2016). Precautionary saving over the business cycle. *The Economic Journal*, 126(590):135–164.

Christelis, D., Georgarakos, D., Jappelli, T., Pistaferri, L., and Van Rooij, M. (2019). Asymmetric consumption effects of transitory income shocks. *The Economic Journal*, 129(622):2322–2341.

Christelis, D., Georgarakos, D., Jappelli, T., and van Rooij, M. (2020). Consumption uncertainty and precautionary saving. *Review of Economics and Statistics*, 102(1):148–161.

Coibion, O., Georgarakos, D., Gorodnichenko, Y., and Weber, M. (2020). Forward guidance and household expectations. Technical report, National Bureau of Economic Research.

Coibion, O. and Gorodnichenko, Y. (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy*, 120(1):116–159.

Conlon, J. J., Pilossoph, L., Wiswall, M., and Zafar, B. (2018). Labor market search with imperfect information and learning. Technical report, National Bureau of Economic Research.

Crawley, E. (2019). In Search of Lost Time Aggregation. Technical Report 2019-075, Board of Governors of the Federal Reserve System (US).

Crawley, E., Holm, M., and Tretvoll, H. (2022). A parsimonious model of idiosyncratic income.

Crump, R. K., Eusepi, S., Tambalotti, A., and Topa, G. (2022). Subjective intertemporal substitution. *Journal of Monetary Economics*, 126:118–133.

Davis, S. J. and Von Wachter, T. M. (2011). Recessions and the cost of job loss. Technical report, National Bureau of Economic Research.

De Nardi, M. (2015). Quantitative models of wealth inequality: A survey.

Den Haan, W. J., Rendahl, P., and Riegler, M. (2018). Unemployment (fears) and deflationary spirals. *Journal of the European Economic Association*, 16(5):1281–1349.

Dominitz, J. and Manski, C. F. (1997). Using expectations data to study subjective income expectations. *Journal of the American statistical Association*, 92(439):855–867.

Dräger, L. and Nghiem, G. (2021). Are consumers' spending decisions in line with a euler equation? *Review of Economics and Statistics*, 103(3):580–596.

Drahs, S., Haywood, L., and Schiprowski, A. (2018). Job search with subjective wage expectations.

Druedahl, J., Jørgensen, T., and Graber, M. (2021). High frequency income dynamics. *Available at SSRN 3816424*.

Dynan, K., Elmendorf, D., and Sichel, D. (2012). The evolution of household income volatility. *The BE Journal of Economic Analysis & Policy*, 12(2).

Dynan, K. E., Skinner, J., and Zeldes, S. P. (2004). Do the rich save more? *Journal of political economy*, 112(2):397–444.

Engelberg, J., Manski, C. F., and Williams, J. (2009). Comparing the point predictions and subjective probability distributions of professional forecasters. *Journal of Business & Economic Statistics*, 27(1):30–41.

Epper, T., Fehr, E., Fehr-Duda, H., Kreiner, C. T., Lassen, D. D., Leth-Petersen, S., and Rasmussen, G. N. (2020). Time discounting and wealth inequality. *American Economic Review*, 110(4):1177–1205.

Flavin, M. A. (1988). The Excess Smoothness of Consumption: Identification and Interpretation. Working Paper 2807, National Bureau of Economic Research.

Fujita, S. and Ramey, G. (2009). The cyclicality of separation and job finding rates. *International Economic Review*, 50(2):415–430.

Fuster, A., Kaplan, G., and Zafar, B. (2020). What Would You Do with $500? Spending Responses to Gains, Losses, News, and Loans. *The Review of Economic Studies*. rdaa076.

Gottschalk, P., Moffitt, R., Katz, L. F., and Dickens, W. T. (1994). The growth of earnings instability in the us labor market. *Brookings Papers on Economic Activity*, 1994(2):217–272.

Gourinchas, P.-O. and Parker, J. A. (2002). Consumption over the life cycle. *Econometrica*, 70(1):47–89.

Gregory, V., Menzio, G., and Wiczer, D. (2025). The alpha beta gamma of the labor market. *Journal of Monetary Economics*, 150:103695.

Guiso, L., Jappelli, T., and Terlizzese, D. (1992). Earnings uncertainty and precautionary saving. *Journal of Monetary Economics*, 30(2):307–337.

Guvenen, F. (2007). Learning your earning: Are labor income shocks really very persistent? *American Economic Review*, 97(3):687–712.

Guvenen, F. (2009). An empirical investigation of labor income processes. *Review of Economic Dynamics*, page 22.

Guvenen, F. (2011). Macroeconomics with heterogeneity: A practical guide.

Guvenen, F., Karahan, F., Ozkan, S., and Song, J. (2019). What do data on millions of us workers reveal about life-cycle earnings dynamics? Technical report, Federal Reserve Bank of New York.

Guvenen, F., Karahan, F., Ozkan, S., and Song, J. (2021). What do data on millions of us workers reveal about lifecycle earnings dynamics? *Econometrica*, 89(5):2303–2339.

Guvenen, F., Ozkan, S., and Song, J. (2014). The nature of countercyclical income risk. *Journal of Political Economy*, 122(3):621–660.

Hajdini, I., Knotek, E. S., Leer, J., Pedemonte, M., Rich, R., and Schoenle, R. (2025). Low pass-through from inflation expectations to income growth expectations: Why people dislike inflation.

Harmenberg, K. and Öberg, E. (2021). Consumption dynamics under time-varying unemployment risk. *Journal of Monetary Economics*, 118:350–365.

Heathcote, J. and Perri, F. (2018). Wealth and volatility. *The Review of Economic Studies*, 85(4):2173–2213.

Hendren, N. (2017). Knowledge of future job loss and implications for unemployment insurance. *American Economic Review*, 107(7):1778–1823.

Huggett, M. (1996). Wealth distribution in life-cycle economies. *Journal of Monetary Economics*, 38(3):469–494.

Jain, M., Kostyshyna, O., and Zhang, X. (2024). How do people view wage and price inflation? *Journal of Monetary Economics*, 145:103552.

Kaplan, G., Moll, B., and Violante, G. L. (2018). Monetary policy according to hank. *American Economic Review*, 108(3):697–743.

Kaplan, G. and Violante, G. L. (2010). How much consumption insurance beyond self-insurance? *American Economic Journal: Macroeconomics*, 2(4):53–87.

Kaplan, G. and Violante, G. L. (2014). A model of the consumption response to fiscal stimulus payments. *Econometrica*, 82(4):1199–1239.

Kaplan, G. and Violante, G. L. (2018). Microeconomic heterogeneity and macroeconomic shocks. *Journal of Economic Perspectives*, 32(3):167–94.

Kaplan, G. and Violante, G. L. (2022). The marginal propensity to consume in heterogeneous agent models. Technical report, National Bureau of Economic Research.

Kaplan, G., Violante, G. L., and Weidner, J. (2014). The wealthy hand-to-mouth. *Brookings Papers on Economic Activity*, pages 77–138.

Karahan, F., Mihaljevich, S., and Pilossoph, L. (2017). Understanding permanent and temporary income shocks. https://libertystreeteconomics.newyorkfed.org/2017/11/understanding-permanent-and-temporary-income-shocks/. Accessed: 2017-11-08.

Kaufmann, K. and Pistaferri, L. (2009). Disentangling insurance and information in intertemporal consumption choices. *American Economic Review*, 99(2):387–92.

Kimball, M. S. (1990). Precautionary saving in the small and in the large. *Econometrica*, 58(1):53–73.

Kosar, G. and Melcangi, D. (2025). Subjective uncertainty and the marginal propensity to consume. Technical report, CESifo Working Paper.

Koşar, G. and Van der Klaauw, W. (2025). Workers' perceptions of earnings growth and employment risk. *Journal of Labor Economics*, 43(S1):S83–S121.

Krueger, D., Mitman, K., and Perri, F. (2016). Macroeconomics and household heterogeneity. In *Handbook of Macroeconomics*, volume 2, pages 843–921. Elsevier.

Krusell, P., Mukoyama, T., and Şahin, A. (2010). Labour-market matching with precautionary savings and aggregate fluctuations. *The Review of Economic Studies*, 77(4):1477–1507.

Krusell, P. and Smith, Jr, A. A. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of political Economy*, 106(5):867–896.

Lewis, D., Melcangi, D., and Pilossoph, L. (2024). Latent heterogeneity in the marginal propensity to consume. Technical report, National Bureau of Economic Research.

Low, H., Meghir, C., and Pistaferri, L. (2010). Wage risk and employment risk over the life cycle. *American Economic Review*, 100(4):1432–67.

Ludvigson, S. and Paxson, C. H. (2001). Approximation bias in linearized euler equations. *Review of Economics and Statistics*, 83(2):242–256.

MaCurdy, T. E. (1982). The use of time series processes to model the error structure of earnings in a longitudinal data analysis. *Journal of econometrics*, 18(1):83–114.

Mankiw, N. G., Reis, R., and Wolfers, J. (2003). Disagreement about inflation expectations. *NBER macroeconomics annual*, 18:209–248.

Manski, C. F. (2004). Measuring expectations. *Econometrica*, 72(5):1329–1376.

Manski, C. F. (2018). Survey measurement of probabilistic macroeconomic expectations: progress and promise. *NBER Macroeconomics Annual*, 32(1):411–471.

McKay, A. (2017). Time-varying idiosyncratic risk and aggregate consumption dynamics. *Journal of Monetary Economics*, 88:1–14.

Meghir, C. and Pistaferri, L. (2004). Income variance dynamics and heterogeneity. *Econometrica*, 72(1):1–32.

Meghir, C. and Pistaferri, L. (2011). Earnings, consumption and life cycle choices. In *Handbook of labor economics*, volume 4, pages 773–854. Elsevier.

Moffitt, R. A. (2020). Reconciling trends in us male earnings volatility: Results from a four data set project. Technical report, National Bureau of Economic Research.

Moffitt, R. A. and Gottschalk, P. (2002). Trends in the transitory variance of earnings in the united states. *The Economic Journal*, 112(478):C68–C73.

Moore, J. C. (2008). Seam bias in the 2004 sipp panel: Much improved, but much bias still remains. *US Census Bureau Statistical Research Division Survey Methodology Research Report Series*, 3:2008.

Mueller, A. and Spinnewijn, J. (2021). Expectations data, labor market and job search. *Handbook Chapter (Draft)*.

Mueller, A. I., Spinnewijn, J., and Topa, G. (2021). Job seekers' perceptions and employment prospects: Heterogeneity, duration dependence, and bias. *American Economic Review*, 111(1):324–63.

Nekarda, C. J. (2008). Weekly time series of the us labor market. *Unpublished paper, University of California, San Diego*.

Oh, J. and Rogantini Picco, A. (2025). Macro uncertainty, unemployment risk, and consumption dynamics. *International Economic Review*, 66(1):287–312.

Parker, J. A. and Preston, B. (2005). Precautionary saving and consumption fluctuations. *American Economic Review*, 95(4):1119–1143.

Pischke, J.-S. (1995). Individual income, incomplete information, and aggregate consumption. *Econometrica: Journal of the Econometric Society*, pages 805–840.

Pistaferri, L. (2001). Superior information, income shocks, and the permanent income hypothesis. *Review of Economics and Statistics*, 83(3):465–476.

Primiceri, G. E. and Van Rens, T. (2009). Heterogeneous life-cycle profiles, income risk and consumption inequality. *Journal of monetary Economics*, 56(1):20–39.

Ravn, M. O. and Sterk, V. (2017). Job uncertainty and deep recessions. *Journal of Monetary Economics*, 90:125–141.

Ravn, M. O. and Sterk, V. (2021). Macroeconomic fluctuations with hank & sam: An analytical approach. *Journal of the European Economic Association*, 19(2):1162–1202.

Reis, R. (2006). Inattentive consumers. *Journal of monetary Economics*, 53(8):1761–1800.

Ríos-Rull, J.-V. (1996). Life-cycle economies and aggregate fluctuations. *The Review of Economic Studies*, 63(3):465–489.

Rips, L. J., Conrad, F. G., and Fricker, S. S. (2003). Straightening the seam effect in panel surveys. *Public Opinion Quarterly*, 67(4):522–554.

Rozsypal, F. and Schlafmann, K. (2023). Overpersistence bias in individual income expectations and its aggregate implications. *American Economic Journal: Macroeconomics*.

Ryscavage, P. (1993). The seam effect in sipp's labor force data: Did the recession make it worse?'. Technical report, SIPP working paper.

Sabelhaus, J. and Song, J. (2010). The great moderation in micro labor earnings. *Journal of Monetary Economics*, 57(4):391–403.

Savoia, E. (2023). The effects of labor income risk heterogeneity on the marginal propensity to consume.

Stephens Jr, M. (2004). Job loss expectations, realizations, and household consumption behavior. *Review of Economics and statistics*, 86(1):253–269.

Stoltenberg, C. A. and Uhlendorff, A. (2022). Consumption choices and earnings expectations: empirical evidence and structural estimation.

Storesletten, K., Telmer, C. I., and Yaron, A. (2004). Cyclical dynamics in idiosyncratic labor market risk. *Journal of political Economy*, 112(3):695–717.

Straub, L. (2019). Consumption, savings, and the distribution of permanent income. *Unpublished manuscript, Harvard University*, 17.

Wang, N. (2004). Precautionary saving and partially observed income. *Journal of Monetary Economics*, 51(8):1645–1681.

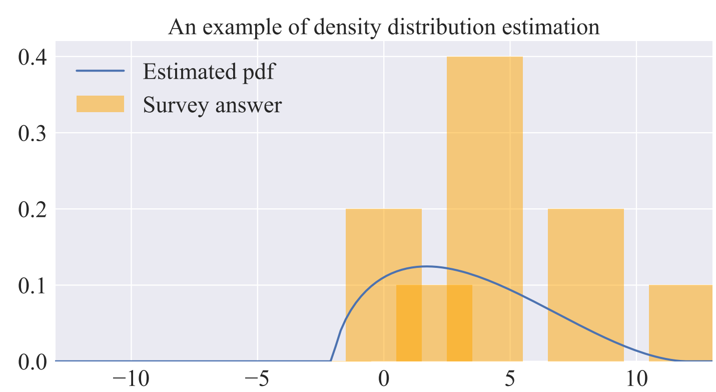
Wang, T. (2022). How do agents form inflation expectations? evidence from the forecast uncertainty. *Unpublished paper, Johns Hopkins University*.

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

A.2. Other facts about wage expectations and perceived risks

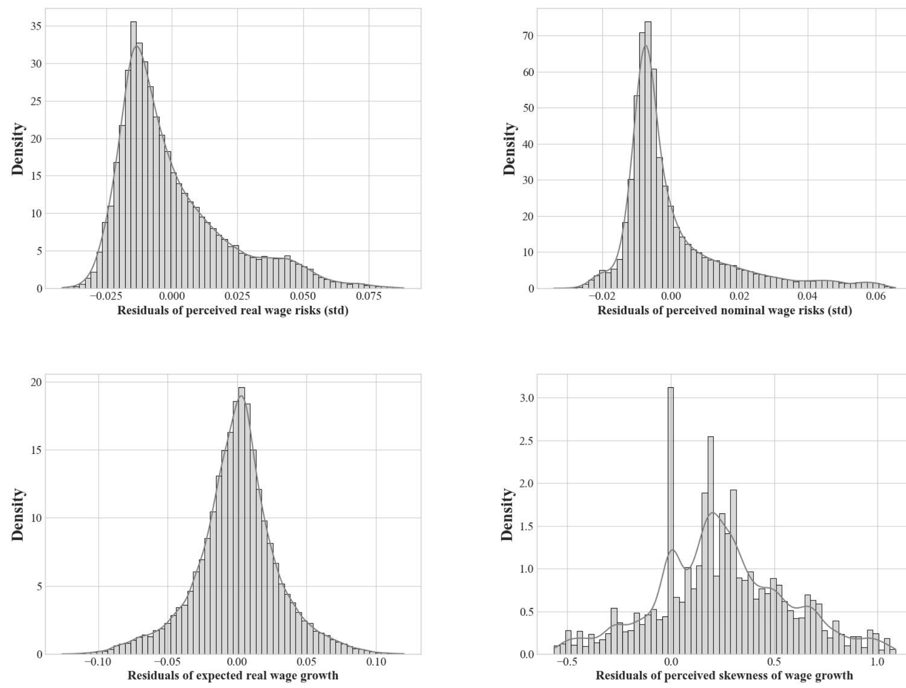
A.2.1. Heterogeneity of perceptions in different moments

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. Machine learning clustering of survey answers

Density forecasts of wage growth in SCE used in this paper's analysis are widely heterogeneous. In addition to indirectly working with the distribution across a set of estimated

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.

moments, I also employ a k-means machine learning algorithm to cluster the density forecasts into heterogeneous types. Figure A.3 plots the average histograms of the 10 types of subjective distribution. The number of clusters, 10, is chosen via k-fold cross-validation. For each type, I report the share of observations belonging to that type, the mean, and the standard deviation based on the same density estimation procedure as in Section A.1. The maximum standard deviation is 0.08, which accounts for only 5.3 % of the SCE observations. Nine out of the ten types have an implied standard deviation that is less than 5%. This assures that the finding of the lower perceived risks than calibrated risks as reported in the main paper is not simply driven by some unusual subsample's unusual behaviors.

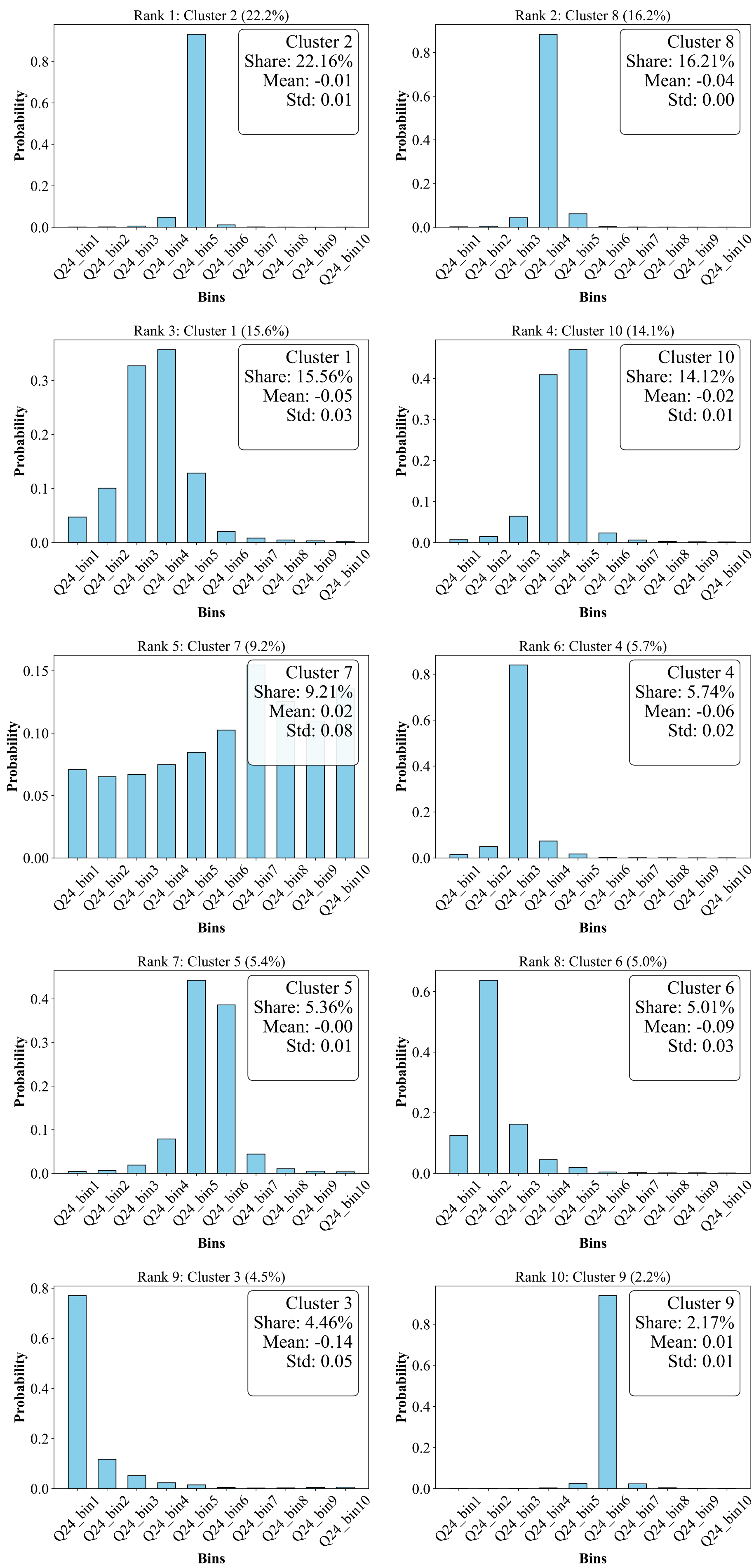
A.3. Wage risk estimation using SIPP data

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 analysis to the SIPP sample based on such a 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.

FIGURE A.3. K-means clustering of the density forecast of wage growth in SCE



- 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.
- 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

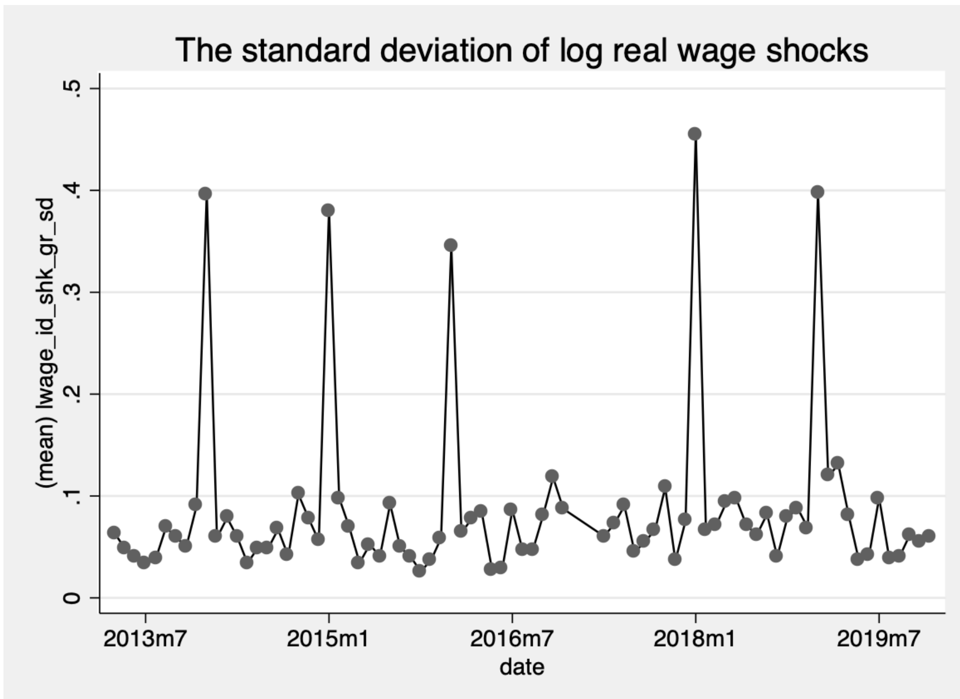
	Obs	Volatility
Year		
2013 (14%)	9,278	N/A
2014 (16%)	12,011	0.41
2015 (12%)	8,853	0.37
2016 (8%)	5,699	0.34
2017 (9%)	6,305	N/A
2018 (11%)	7,877	0.45
2019 (11%)	8,047	0.37
2020 (10%)	7,131	0.35
2021 (4%)	2,974	0.42
Education		
HS dropout (21%)	14,900	0.39
HS graduate (45%)	31,345	0.39
College/above (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 respondent 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.[64]

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 reported.

One way to incorporate the cross-wave 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

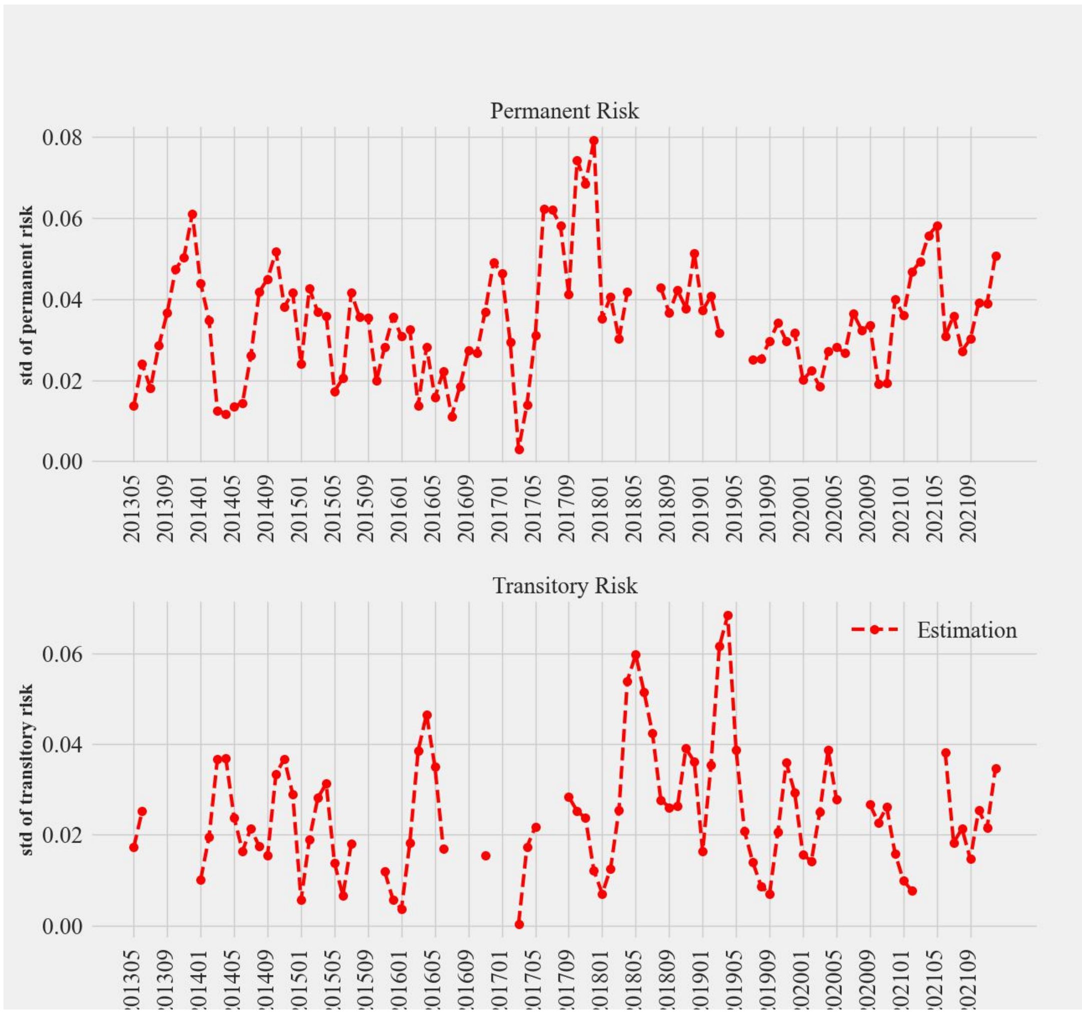
A.4.1. Baseline estimation

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

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

[64]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.

FIGURE A.5. Monthly permanent and transitory wage risks



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

With four consecutive observations of the wages of individual i from $t-2$ to t, hence, three observations of the first residual difference Δe, 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 a 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.

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

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 2.

A.4.2. Converting monthly risks to yearly counterparts

To see how the monthly risk estimates from the procedure above can be aggregated to their annual counterparts as reported in Table 1, define the underlying monthly wage process, as below.

$$y_t = p_t + \theta_t, \tag{A3}$$

$$p_t = p_{t-1} + \psi_t, \tag{A4}$$

where ψ_t is a permanent (random-walk) innovation with variance $Var(\psi_t) = \sigma^2_\psi$ and θ_t is an iid transitory shock with variance $Var(\theta_t) = \sigma^2_\theta$.

Annual wage is observed as the *average* of monthly wage ratess:

$$Y_n \equiv \frac{1}{12} \sum_{m=1}^{12} y_{n,m}. \tag{A5}$$

Transitory component. Because transitory shocks do not persist across months, the annual transitory component is simply the average of monthly transitory shocks:

$$\bar{\theta}_n = \frac{1}{12} \sum_{m=1}^{12} \theta_{n,m}. \tag{A6}$$

By independence,

$$Var(\bar{\theta}_n) = \frac{1}{12^2} \sum_{m=1}^{12} Var(\theta_{n,m}) = \frac{1}{12} \sigma^2_\varepsilon. \tag{A7}$$

Permanent component. Within year n, permanent income evolves as

$$p_{n,m} = p_{n,0} + \sum_{j=1}^{m} \psi_{n,j}, \qquad m = 1, \ldots, 12, \tag{A8}$$

So the annual average permanent component is

$$\bar{p}_n = \frac{1}{12} \sum_{m=1}^{12} p_{n,m} \tag{A9}$$

$$= p_{n,0} + \sum_{j=1}^{12} \frac{13-j}{12} \psi_{n,j}. \tag{A10}$$

Each monthly permanent shock affects all remaining months of the year, with earlier shocks receiving larger weights in the annual average.

Conditioning on $p_{n,0}$, the variance of the annual permanent innovation is therefore

$$Var(\bar{p}_n \mid p_{n,0}) = \sigma^2_\psi \sum_{j=1}^{12} \left(\frac{13-j}{12} \right)^2 \tag{A11}$$

$$= \sigma^2_\psi \frac{1}{12^2} \sum_{k=1}^{12} k^2 \tag{A12}$$

$$= \sigma^2_\psi \frac{12 \cdot 13 \cdot 25}{6 \cdot 12^2} = \frac{325}{72} \sigma^2_\psi \approx 4.51\, \sigma^2_\psi. \tag{A13}$$

Implication.. Assuming the monthly wage risks only vary across years but remain the same within each year, we can use the average estimated monthly risks to obtain their annual counterparts. In particular, the annual variance of the permanent component is approximately 4.51 times the monthly permanent variance σ^2_ψ, whereas the annual transitory variance is only $\sigma^2_\theta/12$.

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 year 2014, 2015, 2016, and from 2018 to 2021, with the constant transitory variance within 3-year block, 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.

TABLE A.2. Estimated wage risks at lower frequencies

Yearly Permanent	0.324408
Yearly Transitory	0.233421
Quarterly Permanent	0.313773
Quarterly Transitory	0.120022

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

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 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%.

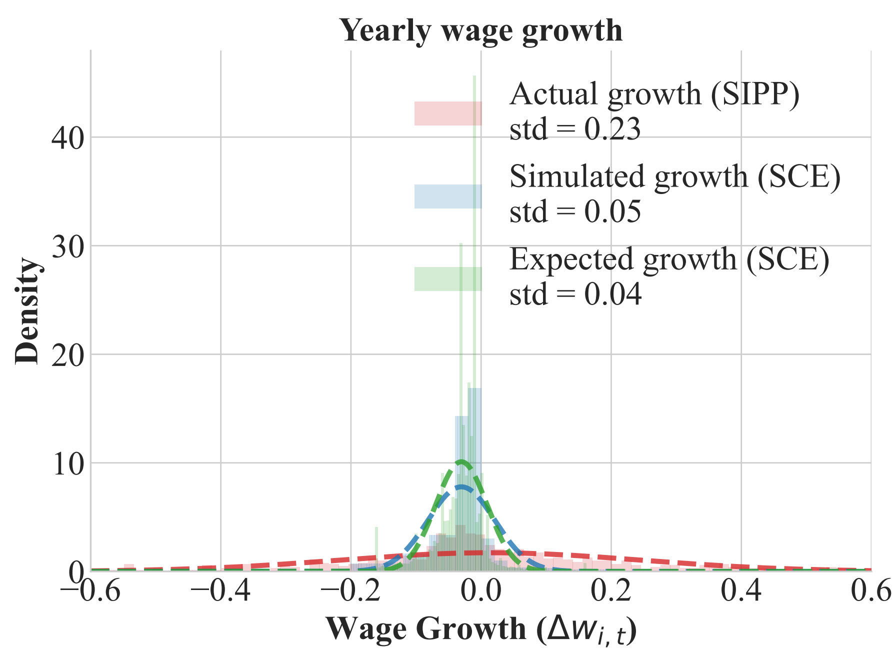
A similar pattern can be seen from the quarterly estimates using quarterly growth of average wage rates (see also Table A.3).

A.5. Perceived versus calibration risks: robustness

A.5.1. A comparison of simulated wage growth from density survey and realized wage growth

A complementary approach to evaluate wage growth expectations and perceived risk is to simulate the distribution of wage growth implied by the full set of individual density forecasts. For each SCE respondent, I draw 1,000 realizations directly from their reported wage-growth histogram and pool these draws to form the implied distribution. This approach is agnostic to any parametric mapping from histogram responses to underlying beliefs. The resulting dispersion reflects both heterogeneity in expected wage growth across individuals and the average perceived risk. I also construct a counterfactual distribution that isolates heterogeneity in expectations by abstracting from perceived risk. Comparing these simulated distributions with the realized wage growth distribution in SIPP reveals a clear pattern: the survey-implied dispersion is far smaller than the actual dispersion in SIPP, and the version based solely on expectational heterogeneity is even slightly narrower, underscoring the modest perceived risks in the survey data.

FIGURE A.6. Simulation of wage growth rate: survey versus panel



This figure compares three wage-growth distributions: (i) the simulated distribution based on 1,000 draws from each respondent's SCE histogram forecast, (ii) the actual wage-growth distribution from SIPP, and (iii) the distribution of expected wage growth reported in the SCE. Each distribution is also shown with its corresponding normal fit.

A.6. Homogeneous and heterogeneous life-cycle wage profiles

Figure A.7A plots the deterministic wage profile used to calibrate the baseline model, which is estimated based on the SCF total wage income. Figure A.7B plots the heterogeneous wage profiles calibrated to the subjective model. Figure A.8 plots the heterogeneous wage profiles used in other model experiments, which are calibrated based on the heterogeneous wage growth rates reported in the SCE.

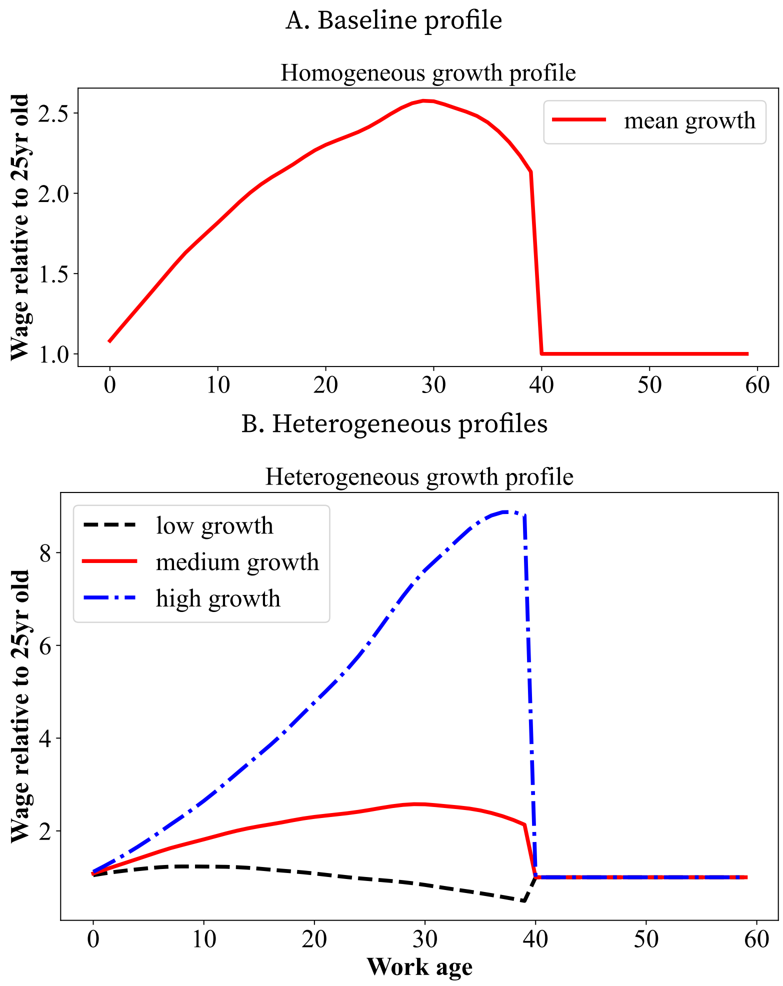
A.7. Other model moments

Figure A.9 plots the other model-implied moments relative to their data counterparts, whenever available. They include the distribution of MPCs across agents, the average life-cycle profile of the expected consumption growth factor, and the distribution of the expected consumption growth factor.

A.8. Income risks in the existing literature

Table A.3 summarizes the most common estimates of income risks seen in the literature. For comparison, I convert all of the risks into 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 instead of a permanent component, I treat the assumed size of the

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



Note: The top and bottom panels, respectively, plot the homogeneous and heterogeneous life cycle profiles of permanent wage growth. The homogeneous profile is based on a regression of fourth-order age polynomials of the real wage income in 2016 SCF, controlling for education, occupation, gender, etc. The post-retirement profile is assumed to stay flat after a one-time drop. The heterogeneous profiles are calibrated to be consistent with the estimated heterogeneity $\sigma_{\xi,\psi} = 0.028$.

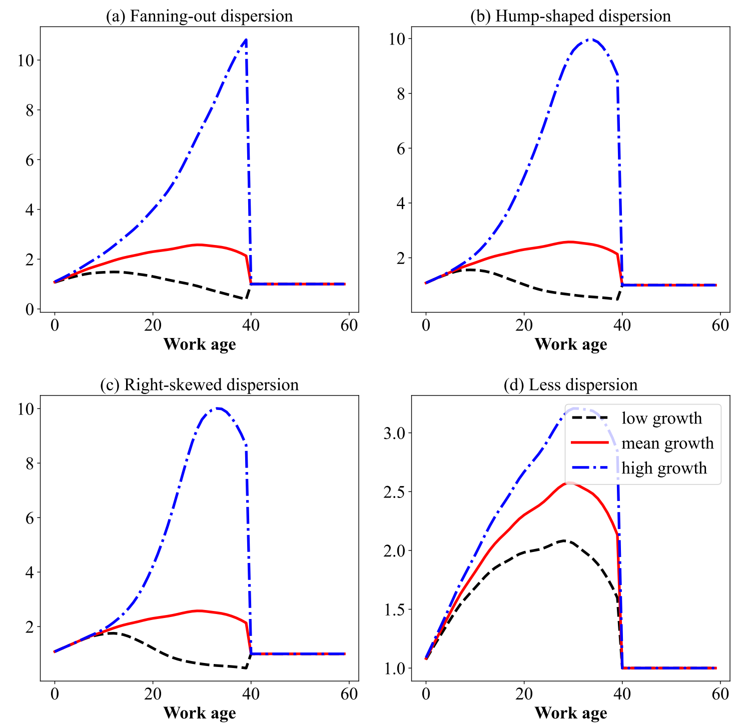
persistent risks as a lower bound for the permanent risks.[65] For models with income risks dependent on aggregate business cycles, a la Krusell and Smith (1998), I compute the steady-state size of the idiosyncratic risks by using the transition probabilities of the aggregate economy employed in the paper.

A.9. Model results: robustness

Table A.4 reports the comparison of baseline and subjective model moments under alternative parameter values. In the first case, I use a pair of smaller values of the calibrated permanent and transitory risks, $\sigma_\psi = 0.10$ and $\sigma_\theta = 0.10$, than those used in the baseline. In the second case, I use two set of higher unemployment insurance replacement ratios $\zeta = 0.5$ and $\zeta = 0.7$. In the third case, I alter the relative ratio of subjective perceptions of permanent and transitory risks: $\kappa = 0.1$ and $\kappa = 10$, respectively. In each case, the improvement of the subjective model's empirical fit relative to the baseline model remains significant.

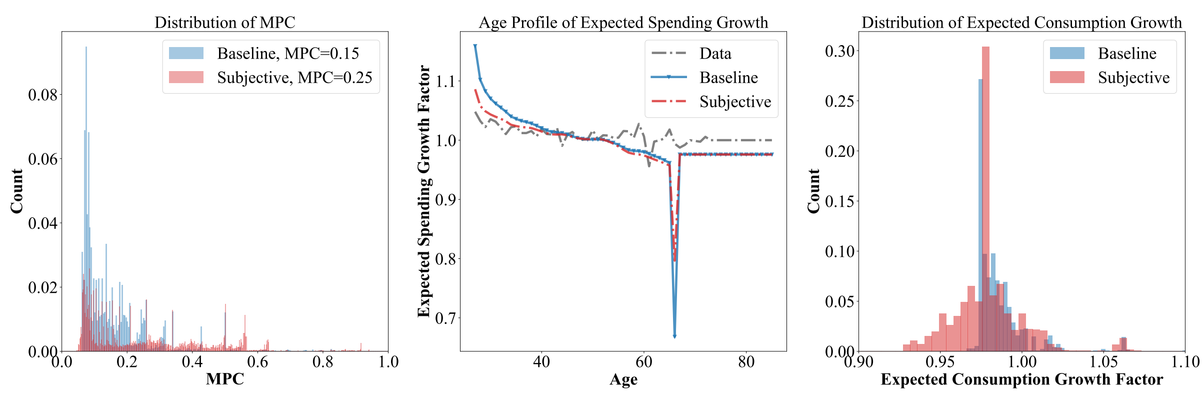
[65]One can think of the permanent income shock as a limiting case of the AR(1) shock, with the persistence parameter infinitely close to 1. The effective income risks increase with the persistence of the shock.

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



Note: These figures plot the profiles of three equally probable heterogeneous deterministic wage profiles that are used to calibrate different model specifications.

FIGURE A.9. Model versus data: other moments



A.10. General equilibrium implications

To complement the model results in the main text, which focus on partial-equilibrium effects, this section provides additional results within a general-equilibrium framework, in the spirit of Huggett (1996); Krueger et al. (2016); Carroll et al. (2017). In this environment, production is endogenous and households' savings serve as the capital input in production. Both the real interest rate and the wage are determined within the model. Beyond the life-cycle consumption–saving problem described in the main text, the remaining elements of the model are described below. I assume there is no aggregate uncertainty in the economy, unlike in Krusell and Smith (1998).

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

$$Y = ZK^{\alpha}N^{1-\alpha} \tag{A14}$$

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

In terms of calibration, 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. 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 based on the equation below.

$$\lambda \left[1 - \Pi^{\mho} + \zeta\Pi^{\mho}\right] = \zeta\Pi^{\mho} \tag{A15}$$

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.

$$\lambda_{SS} \sum_{\tau=1}^{T} \mu_\tau G_\tau (1 - \Pi^{\mho}) = \mathbb{S} \sum_{\tau=T+1}^{L} \mu_\tau G_\tau \tag{A16}$$

Stationary equilibrium. In the absence of the aggregate risk, I focus on the stationary equilibrium of the economy (StE). The stationary equilibrium of the model consists of consumption and savings policies $c(x, \tau)$, $a(x, \tau)$ as well as constant production factor prices, including the real interest rate R and the wage W, the initial wealth of 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:

$$\begin{aligned} c(x, \tau) &= c^*(x, \tau) \\ a(x, \tau) &= a^*(x, \tau) \end{aligned} \tag{A17}$$

2. Distributions $(\psi_1, \psi_2, \ldots, \psi_L)$ are consistent with optimizing household behaviors, as described in Equation 24.

3. The factor markets are clearing.

$$\begin{aligned} \sum_{\tau} \mu_\tau \int_X a(x, \tau) d\psi_\tau &= K \\ \sum_{\tau=1}^{T} \mu_\tau \Pi_\tau^E &= N \end{aligned} \tag{A18}$$

4. Firm optimization under competitive factor markets.

$$W = Z(1-\alpha)(K/N)^{\alpha}$$
$$R = 1 + Z\alpha(K/N)^{\alpha-1} - \delta \tag{A19}$$

5. The initial bank balances of newborns are equal to their accidental bequests

$$b_1 = \sum_{\tau} \mu_\tau D \int_{x\in X} a(x,\tau) R \mathrm{d}\psi_\tau \tag{A20}$$

and

6. The government budget is balanced as described in Equations A15 and A16.

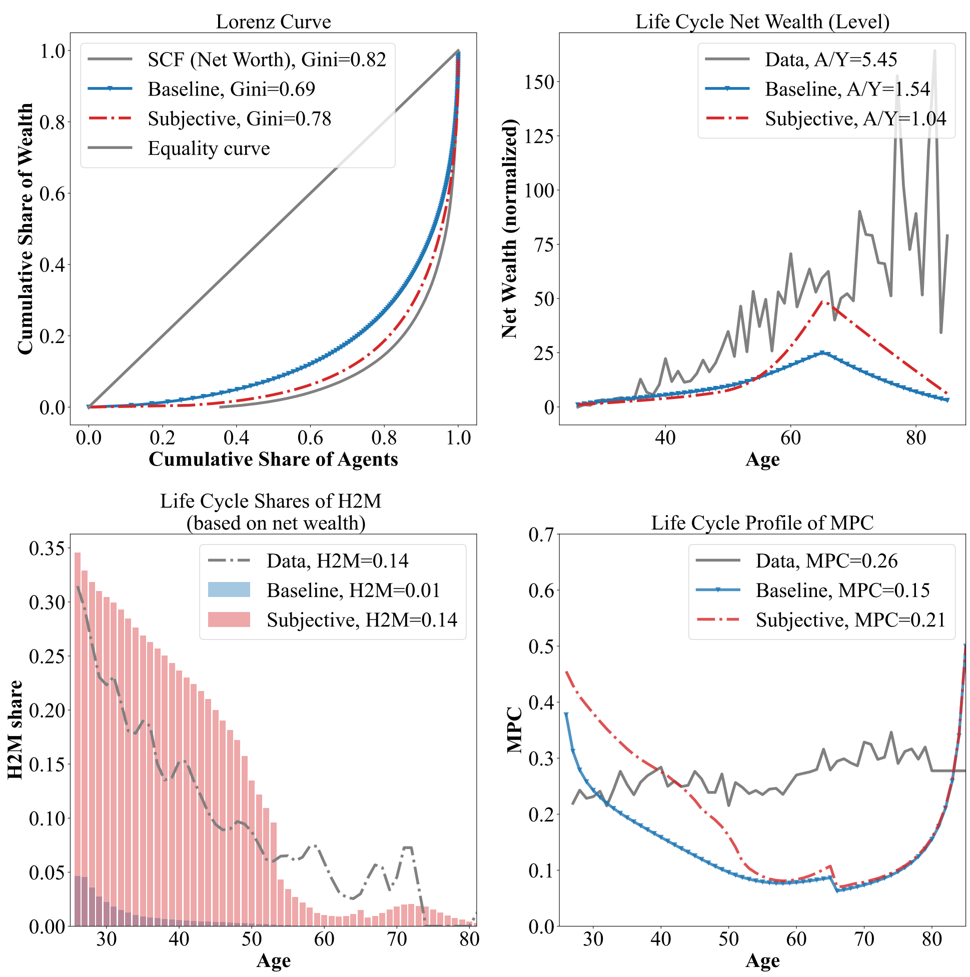
The economy attains different stationary equilibria, depending on the specific assumptions about the size and heterogeneity of income risks Γ. In the subjective model, the stationary equilibrium further depends jointly on $\tilde{\Gamma}$ and Γ and their population distribution.

Results. Figure A.10 presents a comparison between the baseline model and the subjective model in the stationary equilibrium, alongside empirical moments computed under a redefined measure of wealth. Specifically, since savings serve as productive capital in general equilibrium, I use net worth from the SCF—rather than net liquid wealth—to benchmark the partial equilibrium outcomes. Under this definition, the share of H2M households based on net wealth falls to 14%, which is lower than when wealth is measured only by liquid assets. The wealth Gini coefficient falls to 0.81, indicating a slightly reduced degree of underlying inequality relative to the liquid wealth Gini. The average wealth-to-income ratio increases to 5.45, a substantially higher value than the corresponding measure based solely on liquid wealth.

Revisiting the comparison between the baseline and subjective models, the general-equilibrium feedbacks appear to slightly attenuate the effects present in the subjective model under partial equilibrium. Nonetheless, even with this attenuation, the subjective model stays much closer to the redefined data moments. For example, the average H2M share in the subjective model is 0.14—13 percentage points higher than in the baseline model—and exactly matches the data. The life-cycle profile of the H2M share is also largely consistent with the empirical pattern, though the model overstates the proportion of H2M households among the young. The wealth Gini is 9 percentage points closer to its empirical counterpart as well. At the same time, the average wealth-to-income ratio falls short of the baseline value. In both specifications, the resulting mean wealth is too low to match the data, a well-known limitation of the one-asset framework (see Kaplan and Violante (2022) for further discussion).

Table A.5 reports the key moments from the same list of alternative model assumptions in comparison with the data moments calculated based on net worth in SCF. Even in general equilibrium, the improvement in the model's fit with subjective risk beliefs is robust to a list of considerations.

FIGURE A.10. Baseline versus subjective in the general-equilibrium model



Note: The figure displays model-implied moments alongside their empirical counterparts, for both the baseline and the subjective model (*SHPRSUR*) in the general equilibrium. Shown are: the Lorenz curve of household wealth (upper left); life-cycle profiles of average wealth normalized by its value at age 25 (upper right); reported marginal propensities to consume (MPCs) out of a hypothetical $500 windfall (bottom left); and the share of H2M households over the life cycle (bottom right). All wealth statistics are based on total net worth from the 2016 SCF, and reported MPCs are obtained from 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

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

TABLE A.4. Model results: robustness

Model/Data	Gini	Bottom 0.9	Bottom 0.7	Bottom 0.5	Average A/Y	H2M share	Average MPC
Data	0.89	0.15	0.04	0.01	0.74	0.35	0.26
Baseline: σ_ψ = σ_θ= 0.1	0.68	0.43	0.19	0.09	1.33	0.01	0.16
Subjective: σ_ψ = σ_θ=0.1	0.80	0.31	0.09	0.03	0.71	0.20	0.26
Baseline: ζ = 0.5	0.79	0.31	0.11	0.04	1.17	0.12	0.18
Subjective: ζ = 0.5	0.85	0.24	0.05	0.01	0.67	0.30	0.25
Baseline: ζ = 0.7	0.80	0.29	0.09	0.03	1.12	0.18	0.19
Subjective: ζ = 0.7	0.85	0.24	0.05	0.01	0.67	0.32	0.26
Baseline	0.69	0.42	0.18	0.08	1.49	0.01	0.15
Subjective: κ = 0.1	0.78	0.33	0.11	0.04	0.64	0.19	0.25
Subjective: κ = 10	0.83	0.26	0.07	0.02	0.78	0.19	0.25

Note: The table shows, under various alternative values of true wage risks, the unemployment insurance replacement ratio and permanent-to-transitory ratios, 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, the shares of hands-to-mouth agents (H2M), and average MPC in the partial-equilibrium stationary distribution. H2M is defined as those whose liquid wealth is no more than two weeks' (1/24 of annual) income. MPC is calculated in the model as the proportion of a hypothetical one-time $500 windfall spent, as measured in the SCE. Other wealth statistics in the data are computed for both net liquid wealth in the 2016 SCF.

TABLE A.5. Summary of model results and data moments in the general equilibrium

Model/Data	Gini	Bottom 0.9	Bottom 0.7	Bottom 0.5	Average A/Y	H2M share	Average MPC
SCF (net worth)	0.82	0.28	0.08	0.02	5.45	0.14	0.26
Baseline	0.69	0.42	0.18	0.08	1.54	0.01	0.15
Sub. Lower Wage Risk	0.77	0.32	0.12	0.05	1.23	0.02	0.18
Sub. Wage Risk	0.71	0.41	0.17	0.07	1.28	0.02	0.17
Sub. UE risk	0.78	0.32	0.11	0.04	1.30	0.11	0.18
Subjective	0.78	0.34	0.11	0.03	1.04	0.14	0.21
SHPRUR	0.77	0.34	0.11	0.04	1.13	0.12	0.20
HPRSUR	0.74	0.39	0.13	0.04	0.97	0.16	0.21
HPRUR	0.74	0.40	0.13	0.04	1.04	0.13	0.20
Biased Expectation	0.72	0.42	0.15	0.05	1.15	0.13	0.20
Fanning	0.74	0.39	0.13	0.04	0.97	0.16	0.21
Hump	0.74	0.39	0.13	0.04	0.97	0.16	0.21
Right Skew	0.74	0.39	0.13	0.04	0.97	0.16	0.21
CRRA	0.85	0.24	0.05	0.01	1.04	0.20	0.26
Patience	0.78	0.34	0.11	0.03	1.04	0.14	0.21
Bequests	0.79	0.32	0.10	0.03	1.02	0.17	0.22
Borrowing	0.81	0.32	0.08	0.01	1.02	0.22	0.20

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, the shares of hands-to-mouth agents (H2M), and average MPC in the partial-equilibrium stationary distribution under various model specifications in the general equilibrium. H2M is defined as those whose net worth is no more than two weeks' (1/24 of annual) income. MPC is calculated in the model as the proportion of a hypothetical one-time $500 windfall spent, as measured in the SCE. Other wealth statistics in the data are computed for both net worth in the 2016 SCF.