Perceived Income Risks

Tao Wang *

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Abstract

Workhorse incomplete-market macro models typically assume that agents have a perfect understanding of the size and nature of income risks that econometricians estimate from past income data. This paper examines if risk perceptions from a representative density survey align with these assumptions. I found that people have reasonable clues about income risks, in that the differences in risk perceptions can be partly explained by between-group differences in income volatility. Perceived earning risks are always lower than the standard estimates based on realized income volatility, suggesting the role of superior information. At the same time, there remains a large degree of heterogeneity. There is robust evidence for state dependence and past dependence. Risk perceptions countercyclically react to recent realizations and negatively correlated with the experiences of macro labor market outcomes. People also extrapolate their own recent experiences of earning volatility and unemployment when forming risk perceptions. These features in risk perceptions have three macroeconomic consequences. First, lower perceived risks on average helps account for the concentration of low liquid wealth holding among the population. Second, the heterogeneity in risk perceptions leads to additional heterogeneity in saving behavior and marginal propensity to consume (MPC). Third, state-dependent income risk perceptions induce additional precautionary saving motives, and depending on its cyclicality, could further amplify or dampen the business cycle fluctuations of aggregate consumption. My ongoing work explores the quantitative importance of these predictions in a general-equilibrium incomplete market model.

Keywords: Income risks, Incomplete market, Perception, Precautionary saving, Expectation

JEL Codes: D14, E21, E71, G51

*Johns Hopkins University, twang80@jhu.edu. I thank Chris Carroll, Jonathan Wright, Robert Moffitt, Edmund Crawley, Corina Boar, Yueran Ma, and participants of the behavioral economics conference at Yale SOM for useful comments.

1 Introduction

Income risks matter for both individual behaviors and aggregate outcomes. With identical expected income and homogeneous risk preferences, different degrees of risks lead to different saving/consumption and portfolio choices. This is well understood in models in which inter-temporal risk-aversion or prudence (Kimball (1990), Carroll and Kimball (2001)) induces precautionary savings or the occasionally binding constraints result in self-insurance from income risks. It is widely known from the empirical research that idiosyncratic income risks are at most partially insured (Blundell et al. (2008)), such market incompleteness leads to ex-post unequal wealth distribution(Huggett (1993); Aiyagari (1994).) and different degrees of marginal propensity to consume (MPC) (Krueger et al. (2016); Carroll et al. (2017)). This also changes the mechanisms via which macroeconomic policies take into effect[1]. Furthermore, the aggregate movements in the degree of idiosyncratic labor risks drive time-varying precautionary saving motives, as another source of business cycle fluctuations[2].

One important assumption prevailing in incomplete-market macroeconomic models with uninsured risks is that agents have a perfect understanding of the income risks. Under the assumption, economists typically estimate the income process based on micro income data and then treat the estimates as the true model parameters known by the agents making decisions in the model[3]. But given the mounting evidence that people form expectations in ways deviating from full-information rationality, leading to perennial heterogeneity in economic expectations held by micro agents, this assumption seems to be too stringent. To the extent that agents make decisions based on their *respective* perceptions, understanding the *perceived* income risk profile and its correlation structure

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

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

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

with other macro conditions are the keys to explaining both micro and macro economic dynamics.

The theoretical contribution of this paper on this front is to establish a unified framework for perceived income risks under different possible income processes seen in the macro literature. Under a clearly specified income process, I can examine to what extent the perceived income risks align with a number of benchmark predictions under full-information rational expectation(FIRE) and with a list of empirically documented facts regarding the income risk dynamics. For instance, is there a large degree of dispersion in risk perceptions among agents who the modelers assume face the same level of risks? Other questions I use the survey to answer include: are perceived risks state-dependent and counter-cyclical? Do people extrapolate and overreact to recent experiences when forming risk perceptions? Does the perceived risk reflect a reasonably good understanding of the income risks of different nature? The answers to all of these questions are yes.

Individuals of varying characteristics face potentially different income processes. Even under the same income process, the realizations of income differ across agents due to differences in realized shocks. In addition to the fact that realized income is not observed in these surveys, this makes it additionally challenging to undertake comparisons between perceptions and the underlying process in a similar manner as for expectations about macroeconomic variables such as inflation. A clear comparison of such spirit is also possibly sensitive to the consistency between the frequency of the reported income perception and the frequency of the underlying income process, i.e. the time aggregation problem. Besides, I also explicitly take into account the presence of the superior information problem extensively discussed in the literature.

After clarifying these issues in the theory, I proceed to establish the empirical facts regarding income risk perceptions. Spefically, I utilize the recently available density forecasts of labor income surveyed by New York Fed's Survey of Consumer Expectation (SCE). What is special about this survey is that agents are asked to provide histogram-type forecasts of their earning growth over the next 12 months together with a set of expectational questions about the macroeconomy. When the individual density forecast is available, a parametric density estimation can be made to obtain the individual-specific subjective distribution. And higher moments reflecting the perceived income risks such as variance, as well as the asymmetry of the distribution such as skewness allow me to directly characterize the perceived risk profile without relying on external estimates from cross-sectional microdata. This provides the first-hand measured perceptions on income risks that are truly relevant to individual decisions.

Perceived income risks exhibits a number of important patterns that are consistent with the predictions of my model of experience-based learning with subjective attribution.

- Higher experienced volatility is associated with higher perceived income risks. This helps explain why perceived risks differ systematically across different generations, who have experienced different histories of the income shocks. Besides, perceived risks declines with one's age.

- Perceived income risks have a non-monotonic correlation with the current income, which can be best described as a skewed U shape. Perceived risk decreases with current income over the most range of income values follwed by an uppick in perceived risks for high-income group.

- Perceived income risks are counter-cyclical with the labor market conditions or broadly business cycles. I found that average perceived income risks by U.S. earners are negatively correlated with the current labor market tightness measured by wage growth and unemployment rate. Besides, earners in states with higher unemployment rates and low wage growth also perceive income risks to be higher. This bears similarities to but important difference with a few previous studies that document the counter-cyclicality of income risks estimated by cross-sectional microdata (Guvenen et al. (2014), Catherine (2019)).

- Perceived income risks translate into economic decisions in a way consistent with precautionary saving motives. In particular, households with higher income risk perceptions expect a higher growth in expenditure, i.e. lower consumption today versus tomorrow.

These patterns suggest that individuals have a roughly good yet imperfect understanding of their income risks. Good, in the sense that subjective perceptions are broadly consistent with the realization of cross-sectional income patterns. This is attained in my model because agents learn from past experiences, roughly as econometricians do. In contrast, subjective perceptions are imperfect in that bounded rationality prevents people from knowing about the true size and nature of income shocks as well some parameters of the process perfectly. If hardworking economists equipped with advanced econometric techniques and a large sample of income data do not necessarily specify the income process correctly, it is feasible to admit the agents in the model to be subject to the same difficulty.

As illustrated by much empirical work of testing the rationality in expectations, it is admittedly challenging to separately account for the differences in perceptions driven by the "truth" and the part driven by the pure subjective heterogeneity. The most straightforward way seems to be to treat econometricians' external estimates of the income process as the proxy to the truth, for which the subjective surveys are compared. But this approach implicitly assumes that econometricians correctly specify the model of the income process and ignores the possible superior information that is available only to the people in the sample but not to econometricians. The model built in this paper reconciles both possibilities by modeling agents as bounded rational econometricians subject to model mis-specifications.

Finally, the subjective learning model will be incorporated into an otherwise standard life-cycle consumption/saving model with uninsured idiosyncratic and aggregate risks. Experience-based learning makes income expectations and risks state-dependent when agents make dynamically optimal decisions at each point of the time. In particular, higher perceived risks will induce more precautionary saving behaviors. If this perceived risk is state-dependent on recent income changes, it will potentially shift the distribution of MPCs along income decile, therefore, amplify the channels aggregate demand responses to shocks.

1.1 Related literature

First, this paper closely builds on the literature estimating both cross-sectional and time trends of labor income risks and partial insurance. Early work estimating income risks includes Gottschalk et al. (1994); Carroll and Samwick (1997). Later, the literature explores time-varying patterns of the income risks. For instance, Meghir and Pistaferri (2004) allows for time-varying risks or conditional heteroscedasticity in the traditional permanent-transitory model. Blundell et al. (2008) uses the same specification to income to estimate partial insurance in conjunction with consumption data. More recently, Bloom et al. (2018) found the risks have declined in recent decades. Moreover, recent evidence relied upon detailed social security records and larger data samples highlight the asymmetry and cyclical behaviors of idiosyncratic earning/income risks (Storesletten et al., 2004; Guvenen et al., 2014; Arellano et al., 2017; Guvenen et al., 2019). Besides, a separate literature focus on job-separation and unemployment risks(Low et al., 2010; Davis and Von Wachter, 2011). The novelty of this paper lies in the focus on the subjective perceptions of labor risks and how it is correlated with the realized income risks estimated from the income panel.

Second, it is related to an old but recently reviving interest in studying consumption/saving behaviors in models incorporating imperfect expectations and perceptions. For instance, the closest to the current paper, Pischke (1995) explores the implications of the incomplete information about aggregate/individual income innovations by modeling agent's learning about inome component as a signal extraction problem. Wang (2004) extends the framework to incorporate precautionary saving motives. In a similar spirit, Carroll et al. (2018) reconciles the low micro-MPC and high macro-MPCs by introducing to the model an information rigidity of households in learning about macro news while being updated about micro news. Rozsypal and Schlafmann (2017) found that households' expectation of income exhibits an over-persistent bias using both expected and realized household income from Michigan household survey. The paper also shows that incorporating such bias affects the aggregate consumption function by distorting the cross-sectional distributions of marginal propensity to consume(MPCs) across the population. Lian (2019) shows that an imperfect perception of wealth accounts for such phenomenon as excess sensitivity to current income and higher MPCs out of wealth than current income and so forth. My paper has a similar flavor to all of these works in that I also explore the behavioral implications of households' perceptual imperfection. But it has important two distinctions. First, this paper focuses on higher moments such as income risks. Second, most of these existing work either considers inattention of shocks or bias introduced by the model parameter, none of these explores the possible misperception of the nature of income shocks. [4]

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

[4]For instance, Pischke (1995) assumes that agents know perfectly about the variance of permanent and transitory income so that they could filter the two components from observable income changes. This paper instead assumes that that the agents do not observe the two perfectly.

fore, understanding expectation formation of the individual variables, in particular, concerning both mean and higher moments, will provide fruitful insights for macroeconomic modeling assumptions.

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

Lastly, the idea of this paper echoes with an old problem in the consumption insurance literature: 'insurance or information' (Pistaferri (2001), Kaufmann and Pistaferri (2009),Meghir and Pistaferri (2011)). In any empirical tests of consumption insurance or consumption response to income, there is always a worry that what is interpreted as the shock has actually already entered the agents' information set or exactly the opposite. For instance, the notion of excessive sensitivity, namely households consumption highly responsive to anticipated income shock, maybe simply because agents have not incorporated the recently realized shocks that econometricians assume so (Flavin (1988)). Also, recently, in the New York Fed blog, the authors followed a similar approach to decompose the permanent and transitory shocks. My paper shares a similar spirit with these studies in the sense that I try to tackle the identification problem in the same approach: directly using the expectation data and explicitly controlling what are truly conditional expectations of the agents making the decision. This helps economists avoid making assumptions on what is exactly in the agents' information set. What differentiates my work from other authors is that I focus on higher moments, i.e. income risks and skewness by utilizing the recently available density forecasts of labor income. Previous work only focuses on the sizes of the realized shocks and estimates the variance of the shocks using cross-sectional distribution, while my paper directly studies the individual specific variance of these shocks perceived by different individuals.

2 Theoretical framework

2.1 Income process and risk perceptions

Conditional on employment, log idiosyncratic earning of individual i from group g at time t follows a standard following process (Meghir and Pistaferri (2004)). In general, group g is defined such that within-group workers share the same income process. For instance, it could be defined based on age, gender, education or the years of entering job markets. It contains a predictable component z and an idiosyncratic and stochastical component e. The latter consists of a permanent part ψ, and a transitory part η, which potentially takes a form of MA(1) with persistence of ϕ. Throughout the benchmark discussion in this paper, we assume $\phi = 0$, i.e. zero serial correlation in the transitory component.

$$
\begin{aligned}
y_{i,g,t} &= z_{i,g,t} + e_{i,g,t} \\
e_{i,g,t} &= p_{i,g,t} + \eta_{i,g,t} \\
p_{i,g,t+1} &= p_{i,g,t} + \psi_{i,g,t-1} \\
\eta_{i,g,t+1} &= \phi \epsilon_{i,g,t} + \epsilon_{i,g,t+1}
\end{aligned} \tag{1}
$$

Idiosyncratic shocks ψ and ϵ are normally distributed with zero means and possibly time-varying and group-specific variances denoted as $\sigma^2_{t,g,\psi}$, $\sigma^2_{t,g,\epsilon}$. In the case where risks are equal across all workers, the group subscript g could be dropped.

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

$$
\begin{aligned}
\Delta y_{i,g,t+1} &= \Delta z_{i,g,t+1} + \Delta e_{i,g,t} \\
&= \Delta z_{i,g,t+1} + \psi_{i,g,t+1} + \epsilon_{i,g,t+1} - \epsilon_{i,g,t}
\end{aligned} \tag{2}
$$

All shocks that have realized till t are observed by the agent at time t. Therefore, under full-information rational expectation (FIRE), namely when the agent perfectly knows the income process and parameters, the expected volatility, or what this paper will refer to as perceived risks, is the expected variance of income growth from t to $t+1$.

$$
Var^*_t(\Delta y_{i,g,t+1}) = Var^*_t(\Delta e_{i,g,t+1}) = E_t(\sigma^2_{t+1,g,\psi}) + E_t(\sigma^2_{t+1,g,\epsilon}) \tag{3}
$$

Expected volatility is the sum of conditionally expected permanent risks and transitory risks for time $t+1$ at time t. With constant risks, both expectation signs drop.

Under FIRE, there are a number of testable predictions about the patterns of perceived risks.

- **No within-group disagreement**. First, agents who share the same income process have no disagreements on perceived risks. This can be checked by comparing within-cohort/group dispersion in perceived risks.

- **State-independence**. Second, the perceived risks under such the assumed process above are not dependent on past/recent income realizations. To put it differently, there is no correlation between realized shocks and the perceived risks. This can be tested by estimating the correlation between perceived risks and past income realizations or their proxies if the latter is not directly observed.

- **Correct decomposition**. Third, under the assumed progress, the variances of permanent and transitory shocks enter perceived risks with loadings of 1.

The size of the risks, including the component-specific ones are not directly observable. Econometricians usually estimate them relying upon cross-sectional inequality utilizing information from income panel and take them as the model parameters understood perfectly by the agents. I use econometricians' best estimates from realized income as the proxies of the FIRE perceptions. Assume the unexplained income residuals from this estimation regression is $\hat{e}_{i,t} = y_{i,g,t} - \hat{z}_{i,g,t}$($\hat{z}_{i,g,t}$ is the observable counterpart of $z_{i,g,t}$ from data). The unconditional cross-sectional variance of the change in residuals, usually referred to as the "income volatility" in the literature[5] is equal to the sum of risks of components of different degrees of persistence.

$$Var(\Delta \hat{e}_{i,g,t}) = \hat{\sigma}^2_{t+1,\psi} + \hat{\sigma}^2_{t,\epsilon} + \hat{\sigma}^2_{t+1.\epsilon} \tag{4}$$

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

Combining additional auto-covariance moments of $\Delta\hat{e}_{i,g,t}$, previous work has been able to estimate decomposed time-varying risks of ψ and ϵ[6]. These realized risks $\{\hat{\sigma}^2_{t,\psi}, \hat{\sigma}^2_{t,\epsilon}\} \quad \forall t$ can be then compared to the agents' ex ante expectations of the income volatility.

Notice that a direct comparison between perceived risk $Var_{i,g,t}(\Delta y_{i,g,t+1})$and realized volatility $(\delta\hat{e}_{i,g,t})$ without decomposing realized volatility into different components is sensitive to the underlying income process. This is because economists' estimated volatility is unconditional, while the perception is conditional on the information till time t. Under the aforementioned process, the estimated income volatility also includes the variance from the permanent shock at time t, $\hat{\sigma}^2_{t,\psi}$.

Besides volatility, let's also define the inequality as the cross-sectional variance of the levels of the residuals, which is denoted by $Var(\hat{e}_{i,t})$. Different from growth volatility, it includes the cumulative impacts from all the past permanent shocks, i.e. $\hat{\sigma}^2_{t-k,\psi} \quad \forall k = 0, 1, 2...$, all of which are not correlated with the perceived risk under FIRE. Therefore, it only has a weak correlation with perceived risks under FIRE.

Once component-specific risks are estimated, we can compute the realized income volatility from t to $t+1$ $Var_{g,t}(\Delta\hat{e}_{i,g,t})$ by summing $\hat{\sigma}^2_{t+1,\psi}$ and $\hat{\sigma}^2_{t+1,\epsilon}$. Beyond the benchmark model specified above, we also consider a few alternative specifications to the earning process. Appendix report estimation and comparison results based on these alternative assumptions on income process.

There is another complication regarding the FIRE test: the superior information problem. It states that what econometricians treat as income shocks are actually in the information set of the FIRE agents. Think this as when the known characteristics $\hat{z}$ used in the regression only partially captures the true predictable components z. Hence, the variances of the sample residuals $\hat{e}$ and residuals changes $\Delta\hat{e}$ are bigger than its true counterparts and this results in higher estimated risks than what is to be perceived by a FIRE agent. It is true that this leads to a lower correlation between

[6]Plenty of examples for this, for instance, Gottschalk et al. (1994); Carroll and Samwick (1997); Meghir and Pistaferri (2004).

volatility and perceived risks, but it does not alter the prediction about the positive correlation between the two.

3 Data, variables and density estimation

3.1 Data

The data used for this paper is from the core module of Survey of Consumer Expectation(SCE) conducted by the New York Fed, a monthly online survey for a rotating panel of around 1,300 household heads over the period from June 2013 to January 2020, over a total of 80 months. This makes about 95113 household-year observations, among which around 68361 observations provide non-empty answers to the density question on earning growth.

Particularly relevant for my purpose, the questionnaire asks each respondent to fill perceived probabilities of their same-job-hour earning growth to pre-defined non-overlapping bins. The question is framed as "suppose that 12 months from now, you are working in the exact same ["main" if Q11>1] job at the same place you currently work and working the exact same number of hours. In your view, what would you say is the percentage chance that 12 months from now: increased by x% or more?".

As a special feature of the online questionnaire, the survey only moves on to the next question if the probabilities filled in all bins add up to one. This ensures the basic probabilistic consistency of the answers crucial for any further analysis. Besides, the earning growth expectation is formed for exactly the same position, same hours, and the same location. This has two important implications for my analysis. First, these conditions help make sure the comparability of the answers across time and also excludes the potential changes in earnings driven by endogenous labor supply decisions, i.e. working for longer hours. Empirical work estimating income risks are often based on data from received income in which voluntary labor supply changes are inevitably included. Our subjective measure is not subject to this problem and this is a great advantage. Second, the earning expectations and risks measured here are only conditional on non-separation from the current job. It excludes either unemployment, i.e. likely a zero earning, or an upward movement in the job ladder, i.e. a different earning growth rate. Therefore, this only reflects a lower bound for the income risks facing the individuals. I will separately compare unemployment/separation expectations in Section 4.5.

Unemployment and other involuntary job separations are undoubtedly important sources of income risks, but I choose to focus on the same-job/hour earning with the recognition that individuals' income expectations, if any, may be easier to be formed for the current job/hour than when taking into account unemployment risks. Given the focus of this paper being subjective perceptions, this serves as a useful benchmark. What is more assuring is that the bias due to omission of unemployment risk is unambiguous. We could interpret the moments of same-job-hour earning growth as an upper bound for the level of growth rate and a lower bound for the income risk. To put it in another way, the expected earning growth conditional on current employment is higher than the unconditional one, and the conditional earning risk is lower than the unconditional one. At the same time, since SCE separately elicits the perceived probability of losing the current job for each respondent, I could adjust the measured labor income moments taking into account the unemployment risk.

3.2 Density estimation and variables

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

Since subjective moments such as variance is calculated based on the estimated distribution, it is important to make sure the estimation assumptions of the density distribution do not mechanically distort my cross-sectional patterns of the estimated moments. This is the most obviously seen in the tail risk measure, skewness. The assumption of log normality of income process, common in the literature (See again Blundell et al. (2008)), implicitly assume zero skewness, i.e. that the income increase and decrease from its mean are equally likely. This may not be the case in our surveyed density for many individuals. In order to account for this possibility, the assumed density distribution should be flexible enough to allow for different shapes of subjective distribution. Beta distribution fits this purpose well. Of course, in the case of uniform and isosceles triangular distribution, the skewness is zero by default.

Since the microdata provided in the SCE website already includes the estimated mean, variance and IQR by the staff economists following the exact same approach, I directly use their estimates for these moments. At the same time, for the measure of tail-risk, i.e. skewness, as not provided, I use my own estimates. I also confirm that my estimates and theirs for the first two moments are correlated with a coefficient of 0.9.

For all the moment's estimates, there are inevitably extreme values. This could be due to the idiosyncratic answers provided by the original respondent, or some non-convergence of the numerical estimation program. Therefore, for each moment of the analysis, I exclude top and bottom 3% observations, leading to a sample size of around 48,000.

I also recognize what is really relevant to many economic decisions such as consumption is real income instead of nominal income. I use the inflation expectation and inflation uncertainty (also estimated from density question) to convert nominal earning growth moments to real terms. In particular, the real earning growth rate is expected nominal growth minus inflation expectation of the same individuals.

$$E_{i,t}(\Delta y_{i,t}) = E_{i,t}(\Delta y^n_{i,t+1}) - E_{i,t}(\pi_{t+1}) \tag{5}$$

The variance associated with real earning growth, if we treat inflation and nominal earning growth as two independent stochastic variables, is equal to the summed variance of the two. The independence assumption is admittedly an imperfect assumption because of the correlation of wage growth and inflation at the macro level. So it is should be interpreted with caution.

$$Var_{i,t}(\Delta y_{i,t+1}) = Var_{i,t}(\Delta y^n_{i,t+1}) + Var_{i,t}(\pi_{t+1}) \tag{6}$$

As there are extreme values on inflation expectations and uncertainty, I also exclude top and bottom 2% of the observations.

3.3 Labor income data

I use longitudinal data on individual labor earnings from the 2014-2017 and 2018 panels of the Survey of Income and Program Participation (SIPP)[7]. Each panel of the SIPP is designed to be a nationally representative sample of the U.S. population and surveys thousands of workers. The interviews are conducted once a year to collect the individual's monthly earnings and labor force activity[8]. On average, each individual is surveyed for 33 months over the multiple waves of the survey.

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

Given the earning risks expectations regard the single job for the equal hours of work, I divide

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

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

the monthly earning from the primary job by the average hours of work for the same job and use it to estimate income risks. I restrict the sample used for estimating income risks by following criteria. (1) only working-age population between 22-59. (2) only private-sector jobs, excluding government and workers from the public sectors. (3) no days away from work during the reference month without the pay. (4) the same job from the last year. (5) monthly earnings that are greater than 1.9 times or smaller than 0.1 times of the average monthly earning are excluded. This leaves me with an average monthly panel of 1200-2000 individual earners for the sample period 2013m3-2019m12.

4 Perceived income risks: basic facts

4.1 Cross-sectional heterogeneity

This section inspects some basic cross-sectional patterns of the subject moments of labor income. In Figure 1, I plot the distribution of unexplained residuals of perceived income risks both in nominal and real terms after controlling for observable individual characteristics including age, age polynomial, gender, education, type of work, and time fixed effect, respectively.

There remains a sizable dispersion in perceived income risks. In both nominal and real terms, the distribution is right-skewed with a long tail. Specifically, most of the workers have perceived a variance of nominal earning growth ranging from zero to 20 (a standard-deviation equivalence of $4-4.5\%$ income growth a year). But in the tail, some of the workers perceive risks to be as high as $7-8\%$ standard deviation a year. To have a better sense of how large the risk is, consider a median individual in our sample, who has an expected earnings growth of 2.4%, and a perceived risk of 1% standard deviation. This implies by no means negligible earning risk. [9]

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

[FIGURE 1 HERE]

How are perceived income risks different along important dimensions of observable individual characteristics? Empirical estimates of income risks of different demographic groups from microdata have been rare but not non-existant[10]. It is worth asking if subjective risk perceptions exhibit similar between-group differences. This helps evaluate to what extent heterogeneity in risk perceptions partly reflects the actual differences in income risks.

Figure 2 plots both perceived and realized income volatility over the life-cycle. In order to control for the differences in risks between gender and education, I calculate the average within gender and education groups. It is clear that the subjective risk perceptions decline over the life cycle, consistent with the estimated risk from realizations of income. It is important to notice, however, in principle, the reasons for which subjective risk perceptions decline as one age may not be exactly the same as the one for the same pattern of the actual profile. For instance, as one accumulates experience over time, it may also reduce the subjective uncertainty about the income dynamics of themselves.

[FIGURE 2 HERE]

Another important question is how income risk perceptions correlate with the realized labor income. This is unclear in theory because it could depend on both the true income process and the perception formation. For a subsample of around 4000 observations, SCE surveys the annual earning of the respondent along with their risk perceptions. I group individuals into 10 groups based on their reported earning (within the same time) and plot the average risk perceptions against the decile rank in Figure 3. Perceived risks decline as one's earnings increase. This is not exactly

[10] For instance, Meghir and Pistaferri (2004) estimated that the high-education group is faced with higher income risks than the low-education group. This is further confirmed by my estimation using SIPP. In addition, Sabelhaus and Song (2010); Bloom et al. (2018) documented that income risks decrease with age, and vary with current income level in a non-monotonic U-shape.

consistent with the uptick in income risks for the highest income group, as documented by Bloom et al. (2018) using tax records of income. The most likely explanation is that the small sample I used from SCE does not cover actual top earners. The average annual earning of the top income group is between $45,000 and $120,000 in our sample.

[FIGURE 3 HERE]

4.2 Decomposed risks of different nature

[FIGURE 4 HERE]

4.3 Counter-cyclicality of perceived risk

Some studies have documented that income risks are counter-cyclical based on cross-sectional income data. [11] It is worth inspecting if the subjective income risk profile has a similar pattern. Figure 5 plots the average perceived income risks from SCE against the YoY growth of the average hourly wage across the United States, which shows a clear negative correlation. Table 1 further confirms such a counter-cyclicality by reporting the regression coefficients of different measures of average risks on the wage rate of different lags. All coefficients are significantly negative.

[FIGURE 5 HERE]

[TABLE 1 HERE]

The pattern can be also seen at the state level. Table 2 reports the regression coefficients of the monthly average perceived risk within each state on the state labor market conditions, measured by

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

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

[TABLE 2 HERE]

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

4.4 Experiences and perceived risk

[TABLE 3 HERE]

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

Individuals from each cohort are borned in the same year and obtained the same level of their respective highest education. The experienced volatility specific to a certain cohort c at a given time t can be approximated as the average squared residuals from an income regression based on the historical sample only available to the cohort's life time. This is approximately the unexpected income changes of each person in the sample. I use the labor income panel data from PSID to estimate the income shocks. [12] In particular, I first undertake a Mincer-style regression using major demographic variables as regressors, including age, age polynomials, education, gender and time-fixed effect. Then, for each cohort-time sample, the regression mean-squared error (RMSE) is used as the approximate to the cohort/time-specific income volatility.

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

The right figure in Figure 7 plots the (logged) average perceived risk from each cohort c at year t against the (logged) experienced volatility estimated from above. It shows a clear positive correlation between the two, which suggests that cohorts who have experienced higher income volatility also

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

perceived future income to be riskier. The results are reconfirmed in Table 4, for which I run a regression of logged perceived risks of each individual in SCE on the logged experienced volatility specific to her cohort while controlling individuals age, income, educations, etc. What is interesting is that the coefficient of *expvol* declines from 0.73 to 0.41 when controlling the age effect because that variations in experienced volatility are indeed partly from age differences. While controlling more individual factors, the effect of the experienced volatility becomes even stronger. This implies potential heterogeneity as to how experience was translated into perceived risks.

How does experienced income shock per se affect risk perceptions? We can also explore the question by approximating experienced income growth as the growth in unexplained residuals. As shown in the left figure of Figure 7, it turns out that that a better past labor market outcome experienced by the cohort is associated with lower risk perceptions. This indicates that it is not not just the volatility, but also the change in level of the income, that is assymmetrically extrapolated into their perceiptions of risk.

[FIGURE 7 HERE]

In theory, individual income change is driven by both aggregate and indiosyncratic risks. It is thus worth examining how experienced outcome from the two respective source translate into risk perceptions differently. In order to do so, we need to approximate idiosyncratic and aggregate experiences, separately. The former is basically the unexplained income residual from a regression controlling time fixed effect and also time-education effect. Since the two effects pick up the samplewide or groupwide common factors of each calender year, it excludes aggregate income shocks. The difference between such a residual and one from a regression dropping the two effects can be used to approximate aggregate shocks. As an alternative measure of aggregate economy, I use the official unemployment rate. For all aggregate measures, the volatility is correspondingly computed as the variance across time periods specific to each cohort.

Figure ?? plot income risk perceptions against both aggregate and idiosyncratic experiences measured by the level and the volatility of shocks. It suggests different patterns between the aggregate and idiosyncratic experiences. In particular, a positive aggregate shock (both indicated by a higher aggregate income growth, or a lower unexmployment rate) is associated with lower risk perceptions. Such a negative relationship seems to be non-existent at the individual level. What's common between aggregate and idiosyncratic risks is that the volatility of both kinds of experiences are positively correlated with risk perceptions. Such correlations are confirmed in a regression of controlling other individual characteristics, as shown in Table 4. Individual volatility, aggregate volatility and experience in unemployment rates are all significantly positively correlated with income risk perceptions.

4.5 Unemployment risk perceptions

My analysis so far only focuses on the earning risk conditional on employment. But it admittedly only constitutes a lower bound of the labor market risks since major events such as job loss and displacement usually result in more significant changes in labor income and affects household's welfare[13]. In addition, unemployment risks are usually another central input of the incomplete-market macroeconomic models. Similar to the approach with earning risks, the common practice in these models is to model the process of labor market transitions based on externally estimated statistics and assume the agent correctly perceives it within the model. Therefore, by the same token as for the earning risk, this section examines if the survey-reported expectations of job separation align with realized aggregate dynamics revealed from the labor market statistics. Moreover, are perceived unemployment risks extrapolate from recent experiences of aggregate and individual labor

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

market outcomes?

For a fair comparison between perceptions and realizations which are available at different horizons, we cast both probabilities into a continuous-time Poisson rate. Specifically, for the expectation, let the reported probability of separating from the current job in next 12 months be $P_{i,t}(ue_{t+12}|e_t)$, then the corresponding monthly Poisson rate of job-separation $E_{i,t}(s_{t+1})$ is $-log(1 - P_{i,t}(u_{t+12}|e_t))/12$[14]. With the realized month-to-month flow rate estimated from CPS $P(ue_{t+1}|e_t)$, the corresponding realized Poisson rate s_{t+1} is $-log(1 - P(ue_{t+1}|e_t))$.

Figure 6 plots the converted job-separation expectations and realizations against each other. A few important patterns emerge. First, the comparison confirms our earlier findings based on earning risks that individual perceptions did track the aggregate realizations relatively well, assuring us that people's self-reported perceptions are not entirely groundless or naive. But on the other hand, there are systematic differences between perceptions and realizations.

[TABLE 6 HERE]

4.6 Perceived income risk and consumption spending

Finally, how individual-specific perceived risks affect household economic spending decisions? One of the key testable predictions is higher perceived risks should induce precautionary saving motive, hence lowering current consumption, or increasing expected consumption growth. SCE directly surveys the self-reported spending plan, i.e. expected spending growth over the next year, which exactly corresponds to the object of our interest [15]. Therefore, we can evaluate if higher perceived risks translate affects spending plan consistently with precautionary saving motives.

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

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

In general, expected consumption growth with uncertain labor income does not have analytical expression with perceived income risks in it. This is because the optimal consumption paths crucially depends on the income process as well as the nature of this perceived income risks. But under auxiliary assumptions, we could attain a close form expression of expected growth in consumption. Specifically, assume the agent maximizes discounted CRRA utility from consumption with discount rate θ and exogeously given interest factor $1 + r_t$, and the coefficient of relative risk aversion is ρ. Under log normal income process, the expected consumption growth at time t can be approximated as the following when the borrowing constraint is not binding. The expected consumption growth is higher if the borrowing constraint is binding at time t.

$$E_{i,t}(\Delta c_{i,t+1}) \approx \frac{1}{\rho}(r_t - \theta) + \frac{\rho}{2}\sigma^2_{i,t}(c_{i,t+1}) \tag{7}$$

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

$$E_{i,t}(\Delta c_{i,t+1}) \approx \frac{1}{\rho}(r_t - \theta) + \frac{\rho}{2}\kappa^2 var_{i,t}(\Delta y_{i,t+1}) \tag{8}$$

Since $\kappa \leq 1$, an OLS estimate coefficient of expected spending growth on perceived income risks reveals a lower bound of the 1/2 of the size of relative risk aversion ρ. Table 5 reports the regression results of planned log spending growth over the next year on real and nominal perceived income risk in the variance terms[16]. Regardless of the specification, the perceived risk is indeed positively correlated with the expected spending growth as the precautionary saving motive would predict. Specifically, after controlling for individual fixed effect, i.e. discount rate, and time fixed effect i.e. interest rate, each unit increase in perceived variance leads to around a 3 percentage points increase in expected spending growth. This implies an estimated risk aversion coefficient in the range of 6-7. Besides, the precautionary saving motives are weaker for real earning risks than the nominal, but the two are not significantly different from each other.

[TABLE 5 HERE]

5 Risk perceptions, consumption decisions and wealth inequality

5.1 A stylized life-cycle model

[16]There is an important econometric concern when I run regressions of the decision variable on perceived risks due to the measurement error in the regressor used here. In a typical OLS regression in which the regressor has i.i.d. measurement errors, the coefficient estimate for the imperfectly measured regressor has a bias toward zero. For this reason, if I find that expected spending growth is indeed positively correlated with perceived risks, taking into account the bias, it implies that the correlation of the two is greater in size.

5.1.1 Consumer's problem

Each agent i lives for L and works for T ($T \leq L$) periods since entering the labor market, during which he/she earns stochastic labor income y_τ at the work-age of τ. After retiring at age of $T+1$, the agent lives for another $L-T$ periods of life. We assume away aggregate risks in the benchmark model, therefore there is no need to treat calendar time t from working age τ as two separate state variables, hence we suppress time script t. All shocks are idiosyncratic, or to put it differently, specific to the individual i.

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

$$\max \quad \mathbb{E}\left[\sum_{\tau=0}^{\tau=L-1}(1-D)^\tau \beta^\tau u(c_{i,\tau})\right] \tag{9}$$

where $c_{i,\tau}$ represents consumption at the work-age of τ. The felicity function $u(c)$ takes a standard CRRA form with relative risk aversion of ρ: $u(c) = \frac{c^{1-\rho}}{1-\rho}$. [17]

Denote total cash in hand at the beginning of period τ as $m_{i,\tau}$, the end-of-period saving in period τ after consumption as $a_{i,\tau}$, and the bank balance in period τ as $b_{i,\tau}$. Also, assume R is the gross interest factor. Then the consumer starts with some bank balance b_0 in the initial period, and make consumption decisions subject to the following intertermporal budget constraint.

[17] We assume away the bequest motive and preference-shifter along life cycle model without loss of the key insights regarding income risks.

$$
\begin{aligned}
a_{i,\tau} &= m_{i,\tau} - c_{i,\tau} \\
b_{i,\tau+1} &= a_{i,\tau} R \\
m_{i,\tau+1} &= b_{i,\tau+1} + y_{i,\tau+1}
\end{aligned} \tag{10}
$$

In the benchmark model, I impose an external zero borrowing constraint. Without the external borrowing constraint, the agent will still self-imposed a lower bound for a_τ to avoid the extremely painful zero consumption next period in the case of the worst draw of income shocks.

$$a_{i,\tau} \geq 0 \tag{11}$$

5.1.2 Income process

The stochastic labor income during the agent i's career is assumed to follow a slight variant of the standard permanent/transitory income process used in the literature[18] by allowing the possibility of persistent unemployment risks. Specifically, $y_{i,\tau}$ consists of three multiplicative components, one permanent $p_{i,\tau}$, one potentially persistent or transitory $\xi_{i,\tau}$ and the economy-wide wage rate W. The aggregate wage is taken as a constant by the agent in the partial equilibrium. Therefore, it just serves as a scalar for the consumption problem.[19]

$$y_{i,\tau} = p_{i,\tau} \xi_{i,\tau} W \tag{12}$$

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

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

The permanent income component is subject to a mean-one white-noise shock ψ in each period and a constant growth rate G over the life cycle. The constant growth rate assumption can be again easily modified to allow age differences.

$$
\begin{aligned}
p_{i,\tau} &= G p_{i,\tau-1}\psi_{i,\tau} \\
log(\psi_{i,\tau}) &\sim N(-\frac{\sigma^2_\psi}{2}, \sigma^2_\psi)
\end{aligned} \tag{13}
$$

The persistent/transitory shock $\xi_{i,\tau}$ takes different values depending on the transitory or persistent state of unemployment following a Markov process.[20]

$$
\begin{aligned}
\xi_{i,\tau} &= \begin{cases} \mu & \text{if} \quad u_{i,\tau} = 1 \\ \theta_{i,\tau} & \text{if} \quad u_{i,\tau} = 0 \end{cases} \\
log(\theta_{i,\tau}) &\sim N(-\frac{\sigma^2_\theta}{2}, \sigma^2_\theta)
\end{aligned} \tag{14}
$$

where μ is the replacement ratio of the unemployment insurance and $\theta_{i,\tau}$ is the i.i.d. mean-one white noise shock to the transitory component of the income conditional on staying employed.

The transition matrix between employment ($u_{i,\tau} = 0$) and unemployment ($u_{i,\tau} = 1$) is the following

$$
\pi_{i,\tau+1|\tau} = \begin{bmatrix} \mho & 1-\mho \\ 1-E & E \end{bmatrix} \tag{15}
$$

In general, this assumption implies some degree of the persistence of unemployment risks, but it conveniently nests the special case where the unemployment risk is purely transitory when $\mho = 1-E$,

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

meaning the probability of unemployment is not dependent on the current status.

Notice that in the benchmark model laid out here, I assume the all parameters of income risks σ_ψ, σ_θ, $\mho$, and E to be age-invariant (equivalent to time-independent in this setting). By doing this, I avoid making explicit assumptions on the stochastic process of income risks. This is a common practice in the incomplete market macro literature since Gourinchas and Parker (2002). It is also not fundamentally different from assuming a deterministic age-specific risk profile, as in some variants of the models with the life-cycle component. [21] I relax this assumption by considering an explicitly specified stochastic process of the income volatility a la GARCH in the extension of the model (See the Appendix).

5.1.3 Value function and consumption policy

The following value function characterizes the consumer's problem.

$$V_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau}) = \max_{\{c_{i,\tau}\}} \quad u(c_{i,\tau}) + (1-D)\beta\mathbb{E}_\tau\left[V_{\tau+1}(u_{i,\tau}, m_{i,\tau+1}, p_{i,\tau+1})\right] \tag{16}$$

where the three state variables for the agents are current employment status $u_{i,\tau}$, total cash in hand $m_{i,\tau}$ and permanent income $p_{i,\tau}$. $u_{i,\tau}$ drops from the state variables in the special case of purely transitory unemployment shock ($\mho = 1 - E$).[22]

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

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

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

5.2 Subjective risk perceptions

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

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

1. Underestimation of the earning risks (compared to what is assumed to be the truth in the model)
2. Heterogeneity in risk perceptions
3. Extrapolation of recent experiences
4. State-dependence of risk perceptions

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

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

Such an assumption automatically allows for heterogeneity in risk perceptions across different agents at any point of the time. All individuals are distributed between low and high risk-perception states. In one of the extensions, I also admit ex-ante heterogeneity, namely permanent differences in risk perceptions due to individual fixed effects.

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

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

$$\tilde{V}_\tau(\tilde{\Gamma}_\tau, u_\tau, m_\tau, p_\tau) = \max_{\{c_\tau\}} \quad u(c_\tau) + (1-D)\beta \mathbb{E}_\tau \left[\tilde{V}_{\tau+1}(\tilde{\Gamma}_{\tau+1}, u_\tau, m_{\tau+1}, p_{\tau+1})\right] \tag{17}$$

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

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

The distinction between objective and subject risk perception marks the single most important deviation of this paper from existing incomplete-market macro papers. [23] There is a long tradition

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

of explicitly incorporating various kinds of heterogeneity in addition to uninsured idiosyncratic income shocks in these kinds of models to achieve better match with observed cross-sectional wealth inequality. One of the most notable assumptions used in the literature is the heterogeneity in time preferences (Krusell and Smith (1998), Carroll et al. (2017), Krueger et al. (2016)). My modeling approach shares the spirit with and are not mutually exclusive to these existing assumptions on preferential heterogeneity. But, to some extent, perceptual heterogeneity is more preferable as such patterns are directly observed from the survey data, as I show in the previous part of the paper.

A more fundamental justification for such deviations from the full information rational expectation assumption is that risk parameters Γ are not endogenous variables to be realized in the equilibrium of the model. Therefore, the conventional argument in favor of rational expectation assumption, namely equilibrium outcome drives the agents' perceptions to converge to the "truth", does not apply here. So far, the majority workhorse incomplete market macro literature has not incorporated any endogenous mechanisms that determine the level of income risks. The emerging literature that incorporates labor market search/match frictions in these models have, till now, relied upon simplifying assumptions to get tractability. (McKay, 2017; Acharya and Dogra, 2020; Ravn and Sterk, 2021)

5.3 Stationary equilibrium

As the paper's focus is how risk perceptions drive consumption and savings of both individual and aggregate economy, I deliberately keep the supply side of the asset as simple as possible. I simply assume there is a fixed net supply of asset $\bar{A}$ to which the aggregate saving A needs to equalize to clear the market at an equilibrium real interest rate.

Since there is a fraction of the agents in the economy that are dead each period, there is an equal fraction of the total population that newly enter labor markets. The new entrants start with initial wealth b_0, as their predecessors do. Such an assumption guarantees the existence of a stationary age distribution. Under the condition that $G(1-D)<1$, there exists a stationary distribution of wealth in the economy.

Without the aggregate risk, the stationary equilibrium of the economy consists of

- Optimal consumption policies (and the value functions) of all individuals.
- Stationary distribution of agents across all state variables.
- Market clearing in asset market. $A=\bar{A}$

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

5.4 Objective versus subjective risk profiles

The key implications of the model lie in the differences in consumption functions of the agents in the economy. Therefore, this section devotes to presenting a comparison between the consumption policies under different model assumptions.

First, I consider the benchmark model, named objective model, under standard parameterization of income risk parameters Γ and assumes the unemployment risk to be entirely transitory.

The first version of the subjective model allows the transition between low and high risk subjective states, under which the average transitory and permanent earning risk is lower than the standard configurations but with the same objective unemployment risk. Call it subjective state-dependent volatility (SV) model.

The second version of the model further allows the risk perceptions to be dependent upon the idiosyncratic employment status, such that unemployed agents perceive both permanent and transitory risks to be higher than the employed workers do. Call this subjective extrapolation model.

Figure 8 plots the consumption policies under objective and subjective risk profiles, where agents swing between low and high-risk perceptions. For illustration purpose, I assume the perception state is entirely transitory, which explains why the consumption policy do not differ between low-risk and high-risk perceptions. More generally, persistence in risk perceptions would induce differences between the two. Also, I configure the model such that the average permanent and transitory risks are exactly equal to the objective model. To put it differently, the subjective model can be seen as a mean-preserving spread of the risk profiles. Whether the precautionary saving motive is intensified in the subjective model or not depends on the level of wealth. For low level of wealth, consumption of consumption is lower than the objective model, as the consumer takes into account the possibility that the risk perceptions can be higher.

[FIGURE 8 HERE]

Figure 9 further compares the objective model under transitory unemployment risks versus the subjective model in which employment status leads to additional extrapolations in risk perceptions. Specifically, the latter model lets an unemployed worker be with the high-risk perceptions while the employed to be with the low-risk perceptions. This essentially makes the transition matrix Ω exactly equal to Π. I also configure risk parameters specific to each state such that on average it preserves the same size of permanent and transitory risks compared to the objective model. This guarantees the difference between the two model is not induced by change in the average degree of precautionary saving motives.

[FIGURE 9 HERE]

The most obvious pattern seen in the figure is that within the objective model, unemployed workers have less consumption than employed workers. In addition, between the objective and subjective-extrapolation model, an employed worker with lower risk perceptions actually consume less than the employed worker in the objective model.

5.5 Model extensions

5.5.1 Costly adjustment in consumption

In this section, I extend the benchmark consumption model to incorporate an additional discrete choice of costly extensive adjustment. This is meant to introduce one additional mechanism which helps calibrate the model to match a high level of marginal propensity to consume (MPC) seen in the empirical estimates using natural experiments. One recent example of such a model formulation is Fuster et al. (2021).

Two issues are worth clarifying here. First, this costly adjustment can be explicitly micro-founded by various monetary or mental obstacles that prevent agents from making optimal adjustments in consumption from period to period. Regardless of its specific micro foundations, it effectively leads to extensive adjustment in consumption. Second, the assumption also conveniently captures, in the one-asset setting, the essence of implications from costly adjustment of illiquid assets in the two-asset setting, which generates wealthy hands-to-mouth behaviors, as formulated in the (Kaplan and Violante, 2014).

Specifically, I assume that there is a utility cost the agents need to incur χ, when changing the consumption in each period τ. Recognizing this, in each period, the agents need to first make a discrete choice of whether making adjustments to the consumption. In the case of adjustment, the agents solve the optimal consumption optimally. In the case of non-adjustment, the consumption stays at the level as the previous period, since it is the default consumption choice. Note that since the consumer always has the choice of adjustment, this naturally guarantees that in the presence of negative income shock when staying at the same level of consumption is no longer feasible, the agents will adjust the consumption to obey the budget constraints.

The change in the nature of the problem can be summarized by the restated value functions below. I restate the problem only for a consumer with objective risk profiles, as the subjective agent only has idiosyncratic risk perceptions $\tilde{\Gamma}_{i,\tau}$ as one additional state variable.

$$
\begin{aligned}
V_\tau(c_{i,\tau-1}, u_{i,\tau}, m_{i,\tau}, p_{i,\tau}) &= \max \quad \{V^A_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau}) - \chi, V^N_\tau(c_{i,\tau-1}, u_{i,\tau}, m_{i,\tau}, p_{i,\tau})\} \\
V^A_\tau(u_{i,\tau}, m_{i,\tau}, p_{i,\tau}) &= \max_{\{c_{i,\tau}\}} \quad u(c_{i,\tau}) + (1-D)\beta \mathbb{E}_\tau \left[V_{\tau+1}(u_{i,\tau}, R(m_{i,\tau} - c_{i,\tau}) + y_{i,\tau+1}, p_{i,\tau+1})\right] \qquad (18) \\
V^N_\tau(c_{i,\tau-1}, u_{i,\tau}, m_{i,\tau}, p_{i,\tau}) &= u(c_{i,\tau-1}) + (1-D)\beta \mathbb{E}_\tau \left[V_{\tau+1}(c_{i,\tau-1}, u_{i,\tau}, m_{i,\tau+1}, p_{i,\tau+1})\right]
\end{aligned}
$$

where V^A and V^N represent value functions associated with adjustment and non-adjustment. Notice that in the case of non-adjustment, the consumption in previous period becomes an additional state variable. But essentially, there is no choice to be made as to consumption in the case of non-adjustment.

Solving consumption policies with the both intensive and extensive margin choices introduces additional computational challenges. In particular, it results in discrete jumps hence discontinuity in the value function over different values of state variables and the first order condition, namely the Euler equation, is no longer sufficient for the optimality of consumption. Although brutal force value function maximization is able to produce solutions to the model, I adopt the "Discrete Choice Endogenous Grid Algorithm (DCEGM)" introduced by Iskhakov et al. (2017) to speed up the computation. (See Appendix for the detailed steps of the implementation.)

5.5.2 Heterogeneity in time preferences

5.6 Calibration

5.6.1 Estimation of subjective risk profile

5.6.2 Other parameterization

6 Model implications

6.1 Risk-perception heterogeneity and asset distributions

6.2 “MIT shock” of aggregate economy

7 Conclusion

Incomplete-market macroeconomic models that admit uninsured idiosyncratic income risks have become the new paradigm of macroeconomic analysis in the past decade. This paper builds on this vibrant literature by relaxing the long maintained assumption in these models that agents perfectly understand the underlying size of income risks and behave optimally accordingly.

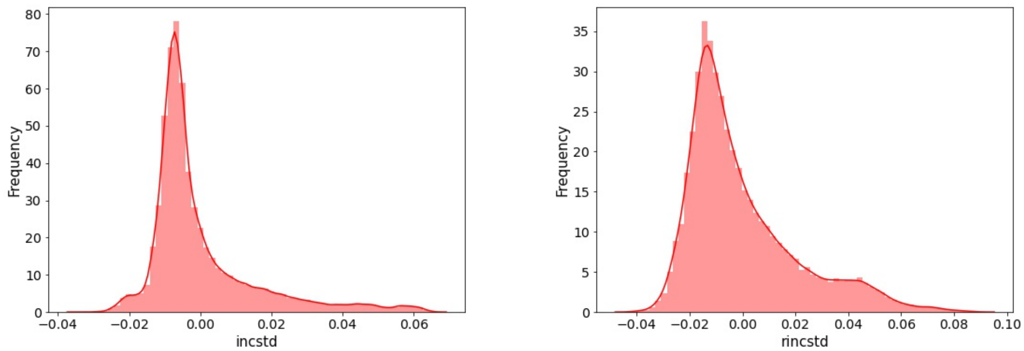
Utilizing the recently available large-scale survey data that elicits density forecast of earnings and labor outcome, I incorporate salient empirical patterns of income risk perceptions such as heterogeneity, extrapolation and state-dependence in these models. The survey evidence also indicates the possible “superior information” problem documented in the literature, confirming an upward bias in the assumed size of income risks in these models compared to what people report in surveys.

This helps explain the low liquid asset holdings of a large fraction of consumers, or the presence of many hands-to-mouth consumers.

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

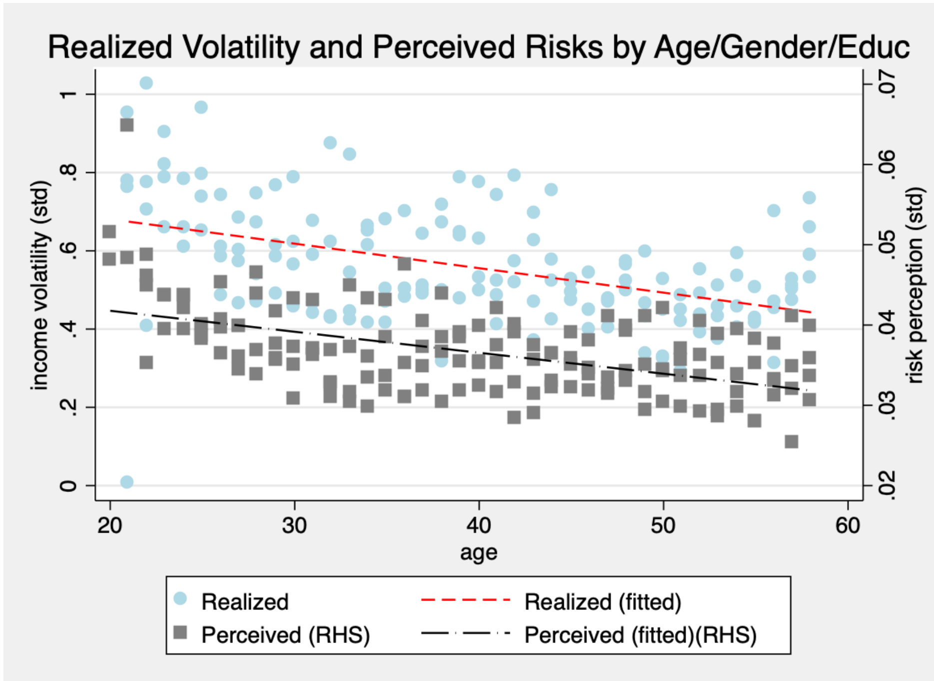
Tables and Figures

Figure 1: Dispersion in Unexplained Perceived Income Risks



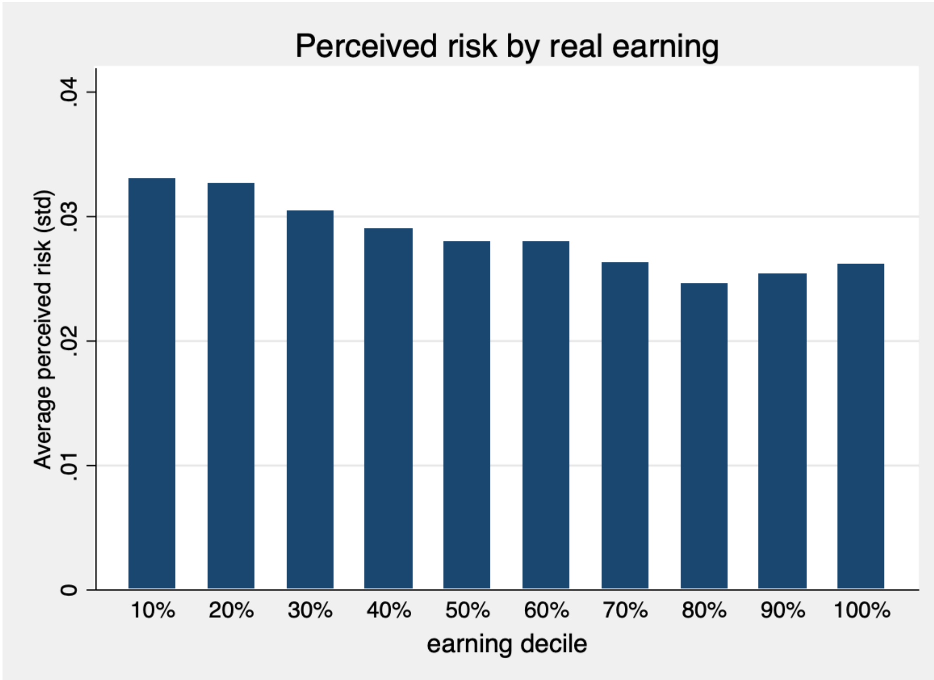
Note: This figure plots the distributions of residuals of the perceived standard deviation of 1-year-ahead earning growth in nominal (left) and real terms (right) after controlling age, age polynomial, gender, education, type of work, and time fixed effects. The real risk is the sum of the perceived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

Figure 2: Realized and Perceived Income Risks over the Life Cycle



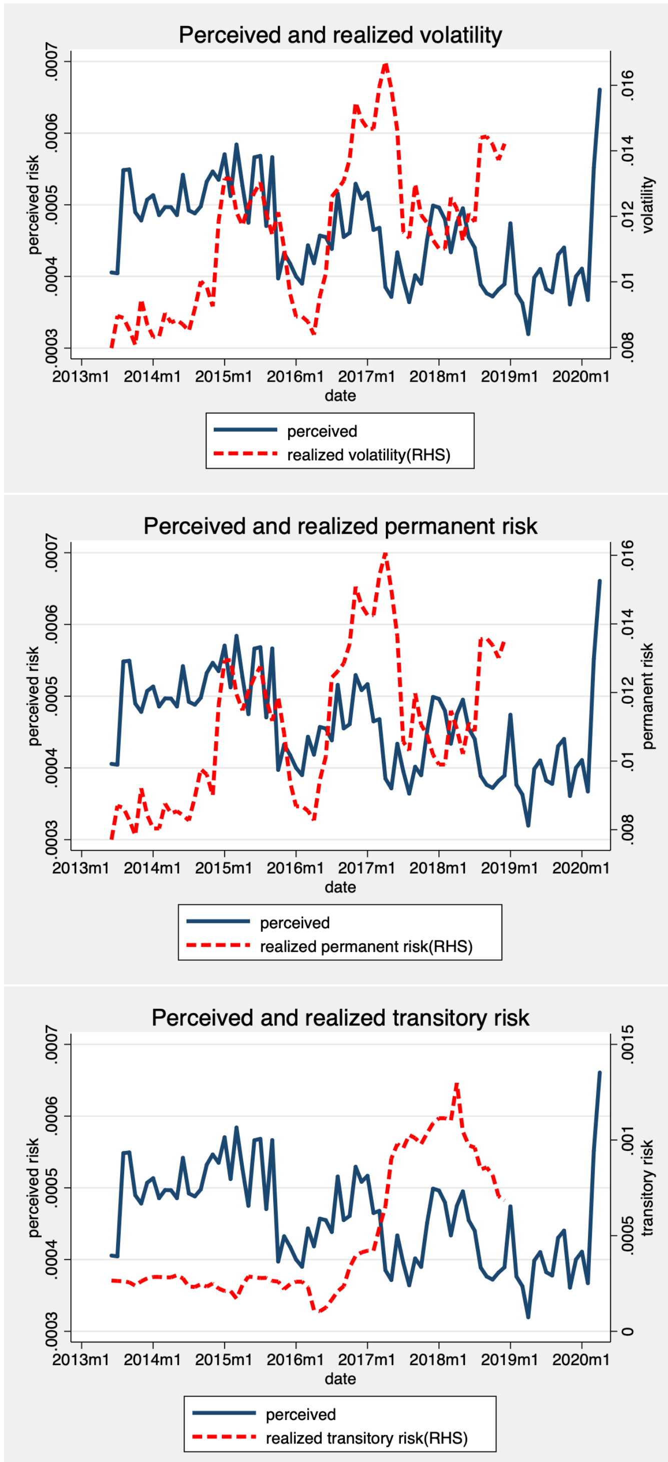
Note: this figure plots average realized income volatility and perceived risks of different age groups. The realized income volatility is approximated by the cross-sectional standard deviation of log changes in unexplained income residuals within age/education/gender group based on PSID.

Figure 3: Perceived Earning Risks by Earning Decile



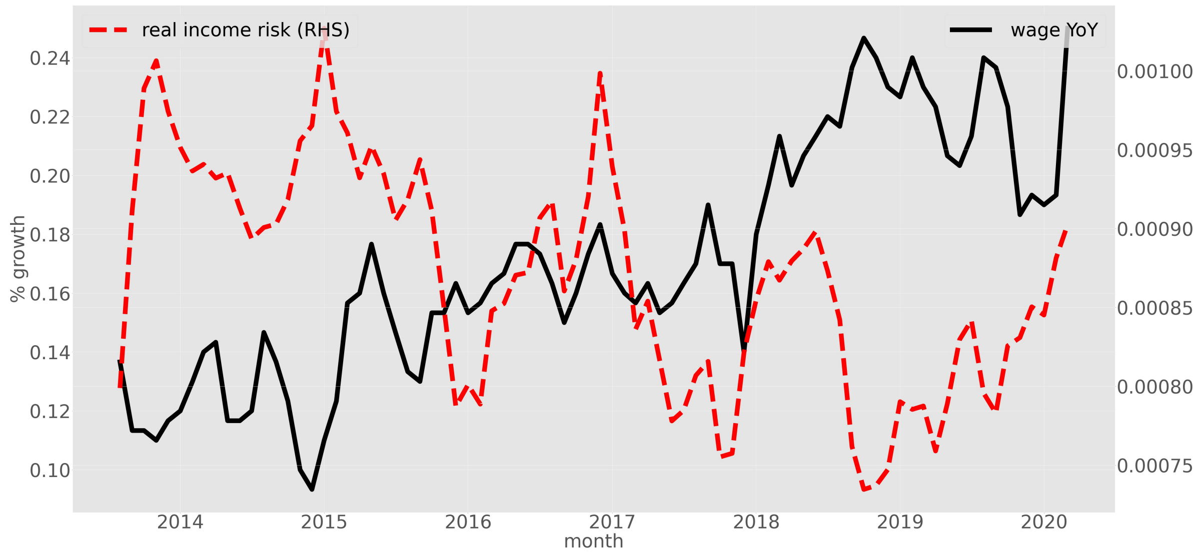
Note: this figure plots average perceived income risks by the decile of annual earning of the same individual.

Figure 4: Perceived and Realized Earning Risks



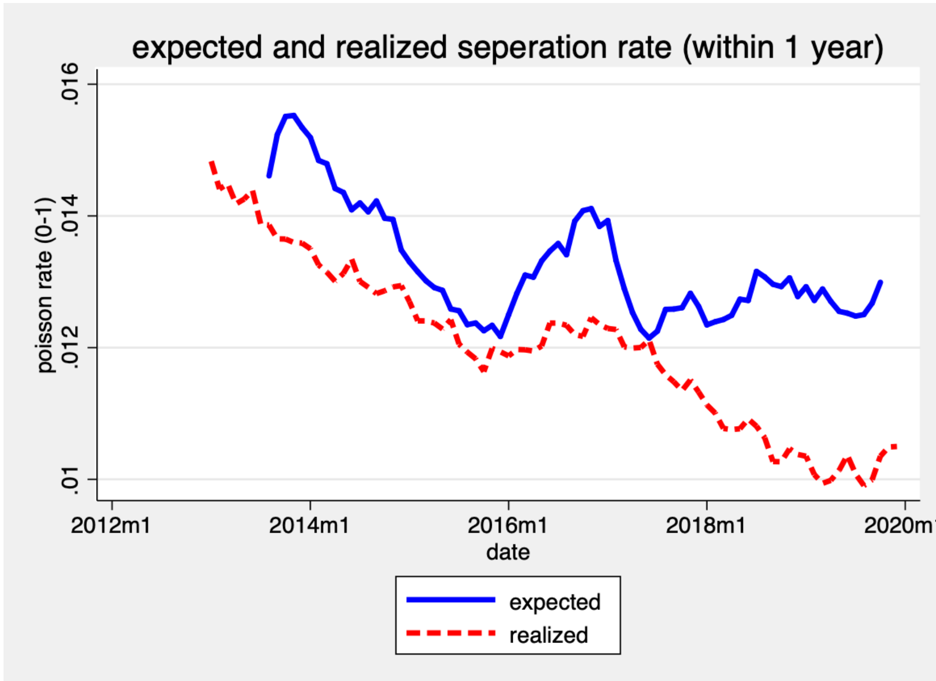
Note: this figure plots median perceived income risks in the whole SCE sample against the realized volatility, permanent, and transitory risks over the same period. The realized risks are first estimated monthly from SIPP and then aggregated into annual frequency. Specifically, the permanent risks are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

Figure 5: Recent Labor Market Conditions and Perceived Risks



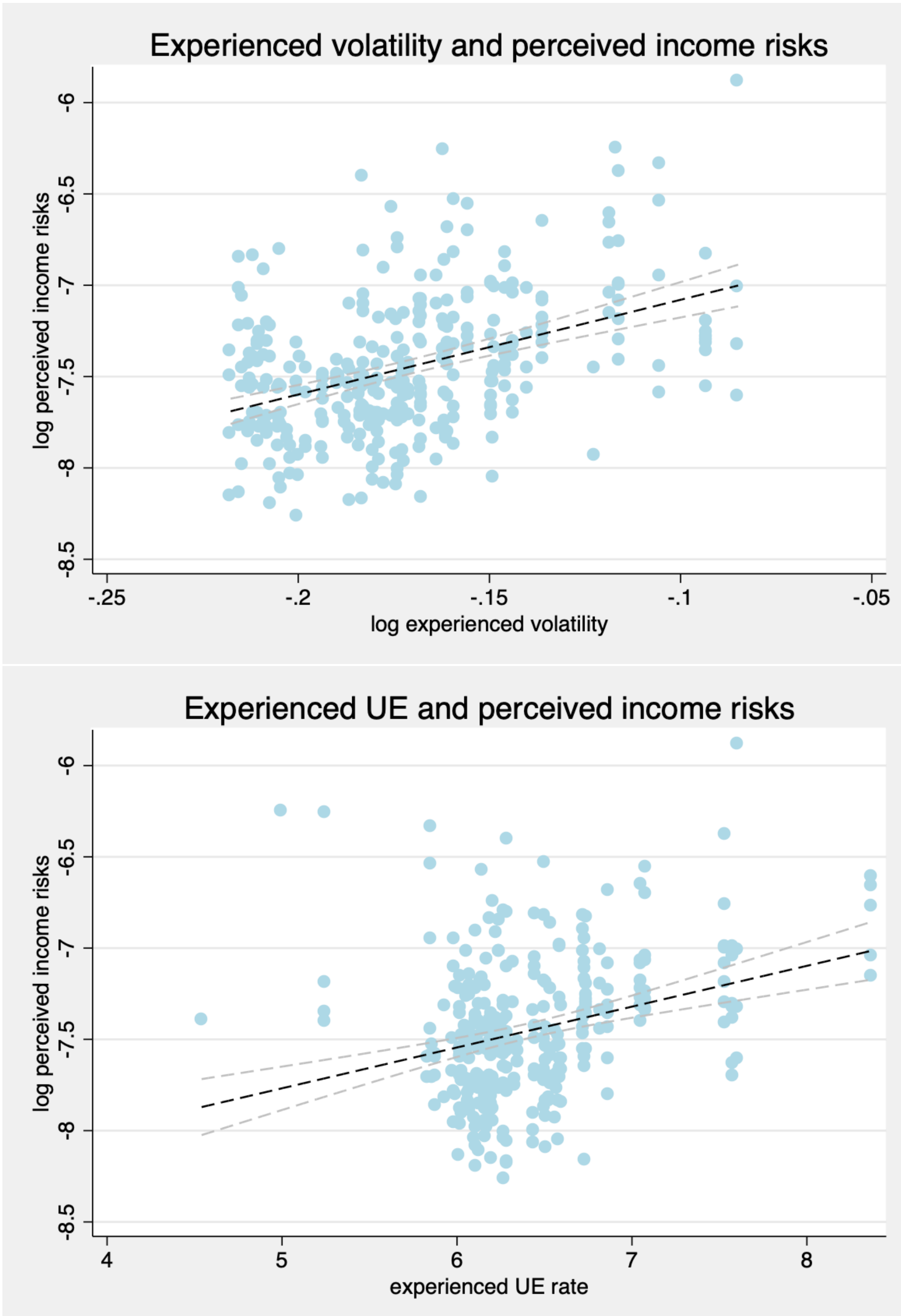
Note: recent labor market outcome is measured by hourly wage growth (YoY). The 3-month moving average is plotted for both series.

Figure 6: Expected and Realized Job-separation rate



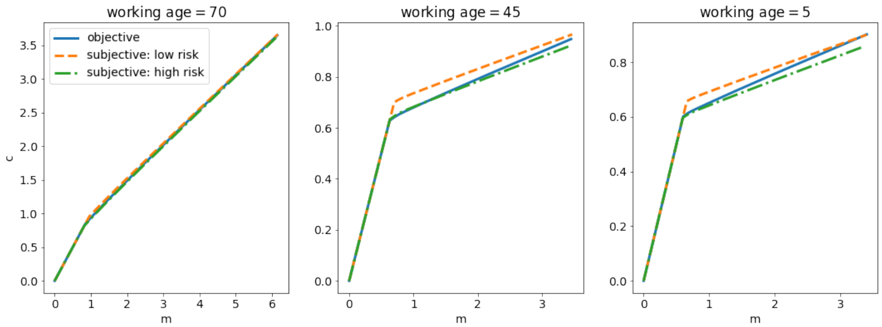
Note: realized job separation rate is computed from CPS. Both are expressed as Poisson arrival rates in continuous time with one month as the unit of time. The 5-month moving average expected rate is plotted.

Figure 7: Experience and Perceived Income Risk



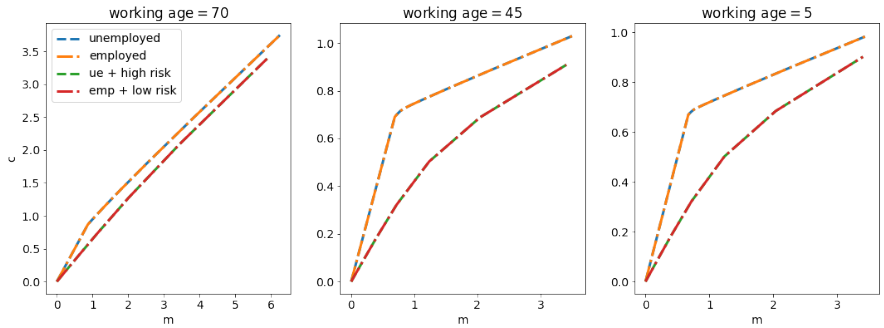
Note: the experienced income volatility is the cross-sectional variance of log change in income residuals estimated using a sub sample restricted to the lifetime of a particular group. For instance, the life experience of a 25-year old till 2015 spans from 1990-2015. The perceived income risk is the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

Figure 8: Consumption functions under objective and subjective risk profiles



Note: this figure plots age-specific optimal consumption policies under objective and subjective state-dependent income risk profiles. The subjective model uses the exact same parameter configurations except for allowing agents to transit between low and high risk perceptions with some degree of persistence. Both the average size of transitory and permanent risks are kept equal to thhat in the objective model.

Figure 9: Consumption functions under objective and state-dependent risk profiles



Note: this figure plots age-specific optimal consumption policies under objective and subjective extrapolative model. The former model includes persistent unemployment risks while the latter maintains the same transition probability of employment status but allows the risk perceptions to be dependent upon the employment status of the individual, i.e. unemployed perceive income risks to be higher than the employed.

Table 1: Current Labor Market Conditions and Perceived Income Risks

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

*** $p<0.001$, ** $p<0.01$ and * $p<0.05$.
This table reports correlation coefficients between different perceived income moments(inc for nominal and rinc for real) at time t and the quarterly growth rate in hourly earning at $t, t-1, ..., t-k$.

Table 2: Average Perceived Risks and State Labor Market

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

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

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

Table 3: Extrapolation from Recent Experience

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

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

Table 4: Perceived Income Risks, Experienced Volatility and Individual Characteristics

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

Standard errors are clustered by household. *** p<0.001, ** p<0.01 and * p<0.05.
This table reports results associated a regression of logged perceived income risks (incvar) on logged idiosyncratic(IdExpVol), aggregate experienced volatility(AgExpVol), experienced unemployment rate (AgExpUE), and a list of household specific variables such as age, income, education, gender, job type and other economic expectations.

Table 5: Perceived Income Risks and Household Spending Plan

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

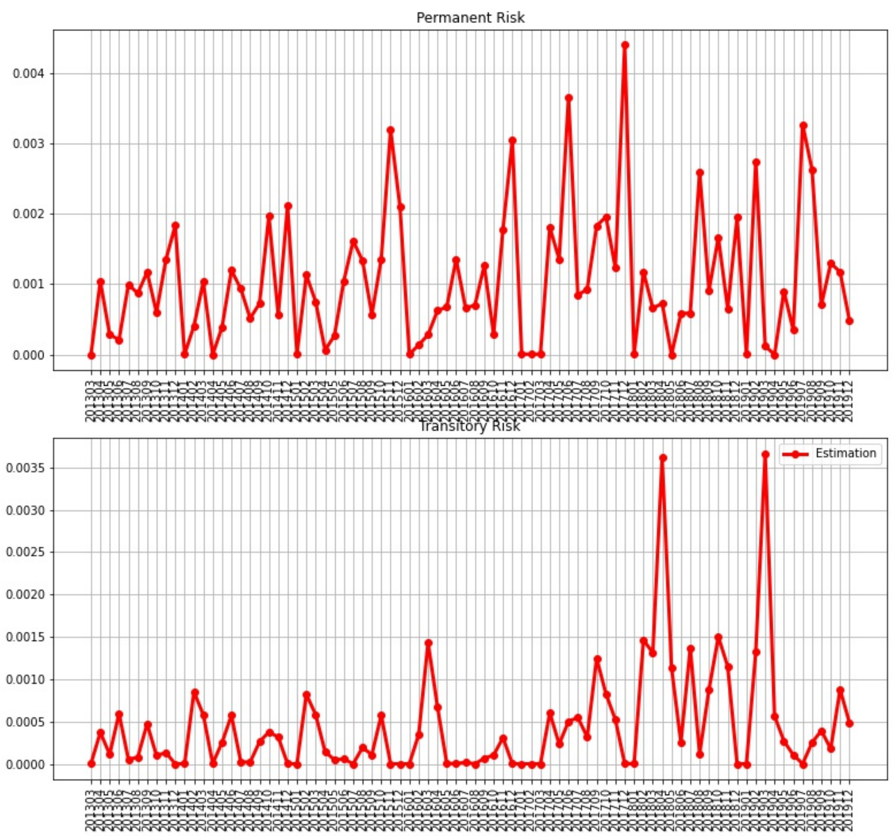
Standard errors are clustered by household. *** p<0.001, ** p<0.01 and * p<0.05.
This table reports regression results of expected spending growth on perceived income risks (incvar for nominal, rincvar for real).

A Online Appendix

A.1 Income risk decomposition under alternative processes

A.1.1 Baseline estimation

Figure A.1: Monthly permanent and transitory income risks



Note: this figure plots the estimated monthly permanent and transitory risks (variances) from SIPP between 2013m3-2017m12.

Table A.1: Estimated realized income risk and perceptions

	PerceivedRisk	PerceivedRisk(median)	RealizedGroupVolatility	RealizedPRisk	RealizedTRisk
full sample (100%)	0.029	0.021	0.090	0.101	0.016
gender					
1 (50%)	0.030	0.022	0.091	0.102	0.016
2 (49%)	0.028	0.022	0.089	0.101	0.016
education					
HS dropout (0%)	0.036	0.022	0.051	0.100	0.016
HS graduate (42%)	0.030	0.022	0.085	0.101	0.016
College/above (56%)	0.028	0.021	0.094	0.101	0.016
5-year age					
20 (2%)	0.037	0.031	0.072	0.102	0.015
25 (12%)	0.032	0.027	0.115	0.102	0.016
30 (12%)	0.030	0.023	0.091	0.101	0.016
35 (13%)	0.029	0.021	0.098	0.101	0.016
40 (13%)	0.028	0.020	0.084	0.101	0.016
45 (14%)	0.028	0.020	0.065	0.101	0.016
50 (15%)	0.027	0.019	0.078	0.101	0.016
55 (15%)	0.027	0.018	0.105	0.100	0.016

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

A.1.2 Infrequent arrival of the transitory shocks

A.1.3 Results with PSID data

A.2 Life-cycle model with stochastic volatility

A.3 Solution algorithms

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