Perceived Income Risks and Subjective Attribution

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Abstract

Heterogenous-agent models with uninsured risks typically assume that agents have a perfect understanding of the size and nature of income risks. This paper explores the implications of the imperfect understanding. I first document the following empirical patterns of subjective risk profile utilizing a density income survey. First, cohorts that experienced higher income volatility perceived higher income risks. Second, earners who are younger, from younger generations and from low-income households have higher perceived risks. Third, perceptions of risks countercyclically react to recent realizations of labor market outcomes. Theoretically, these empirical patterns can be reconciled by a model of learning from past experiences of income realizations based on subjective attribution of the nature of income shocks. By introducing attribution errors due to the psychological tendency to external attribution for bad news and internal attribution for good news, the model provides a consistent explanation for the non-monotonic income-profile of risk perceptions and its countercyclical dynamics.

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 agents are inter-temporally risk-averse, or prudent (Kimball (1990), Carroll and Kimball (2001)), and the risks associated with future marginal utility motivate precautionary motives. Since it is widely known from the empirical research that idiosyncratic income risks are at most partially insured (Blundell et al. (2008)) or because of borrowing constraints, such behavioral regularities equipped with market incompleteness leads to ex-post unequal wealth distribution and different degrees of marginal propensity to consume (MPC). This has important implications for the transmission of macroeconomic policies.

One important assumption prevailing in 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

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the estimates as the true model parameters known by the agents making decisions in the model. 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 with other macro variables are the keys to explaining their behavior patterns.

In theory, this paper constructs a subjective model of learning that features agents' imperfect understanding of the size as well as the nature of income risks. In terms of the size, the imperfect understanding is modeled as a lack of knowledge of the true parameter of an assumed income process. Agents form their best guess about the parameters by learning from the past experienced income of their own as well as others. Such experience-based learning mechanisms engenders the perceived risks to be dependent on age, generation, and macroeconomic history. At the same time, the imperfect understanding of the nature of risks is captured by assuming that individuals do not understand if the income risks are commonly shared aggregate shock or idiosyncratic ones. They learn about the model based on a subjective determination of the nature of the past shocks, which is called *attribution* in this paper. With different subjective attributions, agents arrive at different degrees of model parameter uncertainty, thus different perceptions about income risks.

In a general setting within the model, I show that a higher degree of external attribution, i.e. perceiving the shocks to be common ones instead of idiosyncratic ones, leads to higher risk perceptions. This introduces a well-specified channel through which some imperfect understanding of the nature of shocks leads to differences in risk perceptions. The intuition for this is straightforward. As an econometrician would perfectly understand, learning comes from variations in the sample either cross-sectionally or over time. As agents subjectively perceive the correlation of her own income shocks and others' to be higher, the cross-sectional variation from the sample useful to the learning is reduced, which leads to higehr uncertainty associated with the parameter estimate. I show such a mechanism is generalizable to different assumed income processes such as AR1 or one with permanent/transitory components of time-varying risks.

Incorporating attribution in learning allows it possible to explore the implications of possible mischaracterization of experienced shocks. Among various possible deviations, I explore a particular kind of attribution error which is reminiscent of the "self-serving bias" in the social psychology. In particular, it assumes that people have a tendency to external (internal) attribution in the face of negative (positive) experiences. By allowing the subjective correlation to be a function of the recent experience such as income change, the model neatly captures this psychological tendency. What is interesting is that such a state-dependence of attribution in learning may help explain why the average perceived risk is lower for the high-income groups than the low-income ones. In the presence of aggregate risks, it also generates counter-cyclical patterns of the average perceived risks, i.e. bad times are associated with high subjective risks.

Empirically, the paper sheds light on the perceptions of income risks by utilizing 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))

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 income process perfectly, which even hardworking economists equipped with different advanced econometrical techniques and larger sample of income data cannot easily claim to have.

As illustrated by many empirical work of testing the rationality in expectation formation, 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 econometrician's 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.

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 deciles, therefore, amplify the channels aggregate demand responses to shocks.

1.1 Related literature

From both theoretical and empirical points of view, this paper is an extension of experience-based learning that is developed to account for how experiences shape people's economic expectations and subsequent behaviors. This paper extends the framework in two directions. First, building on the work that shows that experiences affect average expectations, such as inflation (Malmendier and Nagel (2015)) or risky asset return (Malmendier et al. (2019)), I show in the same framework that perceptions of second moments such as income risks can ben influenced by experience in volatility. This is confirmed by the empirical evidence. Second, I introduce the subjective attribution into the framework to allow for the possibility of an imperfect understanding of the nature of the shocks.

Besides, this paper is relevant to four lines of literature. First, it is related to an old but recently reviving interest in studying consumption/saving behaviors in models incorporating imperfect expectations and perceptions. For instance, 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. 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. 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 by exploring the behavioral implications of households' perceptual imperfection. The novelty of my paper lies in the primary focus on higher moments such as risks. Various theories of expectation formation have different predictions about the cross-sectional and dynamic patterns of perceived risks. I examine these predictions in this paper.

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

Third, 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. This will become clear in Section **??**.

2 Data, variables and density estimation

2.1 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. The sample period in my paper spans from June 2013 to June 2019, in a total of 72 months. This makes about 85852 household-year observations, among which around 55,481 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 regarding exactly the same position, same hours, and the same location has two important implications for my analysis. First, these requirements 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. 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 does not fully reflect the entire income risk profile relevant to each individual.

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.

2.2 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 either open-ended bin with positive probability, 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, therefore, use the inflation expectation and inflation uncertainty (also estimated from density question) to convert nominal earning growth moments to real terms for some robustness checks in this paper. In particular, the real earning growth rate is expected nominal growth minus inflation expectation.

$$\overline{\Delta y^r}_{i,t} = \overline{\Delta} y_{i,t} - \overline{\pi}_{i,t} \tag{1}$$

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.

$$\overline{var^r}_{i,t} = \overline{var}_{i,t} + \overline{var}_{i,t}(\pi_t) \tag{2}$$

Not enough information is available for the same kind of transformation of IQR and skewness from nominal to real, so I only use nominal variables. Besides, as there are extreme values on inflation expectations and uncertainty, I also exclude top and bottom 5% of the observations. This further shrinks the sample, when using real moments, to around 40,000.

3 Perceived income risks: basic facts

3.1 Cross-sectional heterogeneity

This section inspects some basic cross-sectional patterns of the subject moments of labor income. In the Figure 1, I plot the distribution of perceived income risks in nominal and real terms, $\overline{var}_{i,t}$ and $\overline{var^r}_{i,t}$, respectively.

There is 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. [1]

[FIGURE 1 HERE]

How are perceived income risks different across a variety of demographic factors? Empirical estimates of income risks of different demographic groups from microdata have been rare[2], not mentioning in subjective risk perceptions. Figure 2 plots the average perceived risks of young, middle-aged, and old workers over the sample period. It is clear that for most of the months, perceived risks decrease with age. Hypothetically, this may be either because of more stable earning dynamics as one is older in the market in reality, or a better grasp of the true income process and higher subjective certainty. The model I will build allows both to play a role.

[FIGURE 2 HERE]

Another important question is how income risk perceptions depend on the realized income. This is unclear ex-ante because it depends on the true income process as well as the perception formation. SCE does not directly report the current earning by the individual who reports earning forecasts. Instead, I use what's available in the survey, the total pretax household income in the past year as a proxy to the past realizations of labor income. As Figure 3 shows, perceived risks gradually declines as one's household income increases for most range of income. But the pattern reverses for the top income group. Such a non-monotonic relationship between risk perceptions and past realizations, as I will show later in the theoretical section, will be reconciled by people's state-dependent attribution and learning.

[FIGURE 3 HERE]

3.2 Counter-cyclicality of perceived risk

Some studies have documented that income risks are counter-cyclical based on cross-sectional data. [3] It is worth inspecting if the subjective income risk profile has a similar pattern. Figure 4 plots the average perceived income risks from SCE against the YoY growth rate of average hourly wage throughout the United States, which shows a clear negative correlation. Table 1 further confirms such a counter-cyclicality by reporting the regression coefficients

[1] 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.

[2] For instance, Meghir and Pistaferri (2004) estimated that high-education group is faced with higher income risks than the low-education group. Bloom et al. (2018) documented that income risks decreases with age and varies with current income level in a U-shaped.

[3] 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.

of different measures of average risks on the wage rate of different lags. All coefficients are significantly negative.

[FIGURE 4 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 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.

3.3 Experiences and perceived risk

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 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. (Oreopoulos et al. (2012)). 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.

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 corresponding panel sample of labor income obtained from PSID. [4] In particular, I first undertake a Miner-style regression using major demographic variables as regressors. I also include the previous-year income to account for persistence in the process. 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 individual 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

[4] 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.

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.

Figure 5 plots the logged average perceived risk from each cohort c at year t against logged experienced volatility estimated from above. It shows a clear positive correlation between the two, which suggests that cohorts who have experienced higher income volatility also perceived future income to be riskier. The results are reconfirmed in Table 3, 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. For instance, each 1 percentage increase in experienced volatility is associated with a 3 to 6 percentage point increase in perceived income risks, depending on the controls included in the regression. What is interesting is that the coefficient of *expvol* declines from 6.31 to 2.92 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 possible potential heterogeneity as to how experience is translated into perceived risks.

[FIGURE 5 HERE]

3.4 Other individual characteristics

What other factors are associated with risk perceptions? This section inspects the question by regressing the perceived income risks at the individual level on four major blocks of variables: experienced volatility, demographics, unemployment expectations by the respondent, as well as job-specific characteristics. The regression is specified as followed.

$$\overline{risk}_{i,c,t} = \alpha + \beta_0 \text{HH}_{i,c,t} + \beta_1 \text{expvol}_{c,t} + \beta_2 \text{Exp}_{i,c,t} + \beta_4 \text{JobType}_{i,c,t} + \epsilon_{i,t} \tag{3}$$

The dependent variable is the individual i from cohort c's perceived risk. Experienced volatility $expvol_{c,t}$ is cohort-and-time-specific. The second type of factors denoted $HH_{i,t}$ represents household-specific demographics such as the age, household income level, education, and gender of the respondent. Third, $Exp_{i,t}$ represents other subjective expectations held by the same individual. As far as this paper is concerned, I include the perceived probability of unemployment herself and the probability of a higher nationwide unemployment rate. The fourth block of factors, as called $Jobtype_{i,t}$ includes dummy variables indicating if the job is part-time or if the work is for others or self-employed.

Besides, since many of the regressors are time-invariant household characteristics, I choose not to control household fixed effects in these regressions (ω_i). Throughout all specifications, I cluster standard errors at the household level because of the concern of unobservable household heterogeneity.

The regression results reported in Table 3 are rather intuitive. From the first to the sixth column, I gradually control more factors. All specifications confirm that higher experienced volatility in the past, workers from low-income households, females, and lower education and self-employed jobs have higher perceived income risks.

In our sample, there are around 15% (6000) of the individuals who report themselves to be self-employed instead of working for others. The effects are statistically and economically significant. Whether a part-time job is associated with higher perceived risk is ambiguous depending on if we control household demographics. At first sight, part-time jobs may be thought of as more unstable. But the exact nature of part-time job varies across different types and populations. It is possible, for instance, that the part-time jobs available to high-income and educated workers bear lower risks than those by the low-income and low-education groups.

Higher perceived the probability of losing the current job, which I call individual unemployment risk, *UEprobInd* is associated with higher earning risks of the current job. The perceived chance that the nationwide unemployment rate going up next year, which I call aggregate unemployment risk, *UEprobAgg* has a similar correlation with perceived earning risks. Such a positive correlation is important because this implies that a more comprehensively measured income risk facing the individual that incorporates not only the current job's earning risks but also the risk of unemployment is actually higher. Moreover, the perceived risk is higher for those whose perceptions of the earning risk and unemployment risk are more correlated than those less correlated.

[TABLE 3 HERE]

3.5 Perceived income risk and decisions

Finally, how individual-specific perceived risks affect household economic decisions such as consumption? The testable prediction is higher perceived risks shall increase precautionary saving motive therefore lower future consumption (higher consumption growth.) Although we cannot directly observe the respondent's spending decisions, we can alternatively rely on the self-reported spending plan in the SCE to shed some light on this.

Table 4 reports the regression results of planned spending growth over the next year on the expected earning's growth (the first column) as well as a number of perceived income risk measures. [5] Each percentage point increase in expected income growth is associated with a 0.39 percentage point increase in spending growth. At the same time, one percentage point higher in the perceived risk increases the planned spending growth by 0.58 percentage. This effect is even stronger for real income risks. As a double-check, the individual's perceived probability of a higher unemployment rate next year also has a similar effect. These results suggest that individuals do exhibit precautionary saving motives according to their own perceived risks.

[TABLE 4 HERE]

[5] There is one 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 will have a bias toward zero. For this reason, if I find that willingness to consume is indeed negatively correlated with perceived risks, taking into account the bias, it implies that the correlation of the two is greater in the magnitude.

4 Model

4.1 Income process and a model of learning

We start by defining an AR(1) process of the individual income. In particular, the income of individual i from the cohort c at time t depends on her previous-period income with a persistence parameter of ρ and an individual and time-specific shock $\epsilon_{i,c,t}$. I define cohort c to be measured by the year of entry in the job market.

$$y_{i,c,t} = \rho y_{i,c,t-1} + \epsilon_{i,c,t} \tag{4}$$

It is assumed that the ρ is the same across all invididuals. Also, I assume the income shock $\epsilon_{i,c,t}$ to be i.i.d., namely independent across individuals and the time,and with an identical variance, as defined in the equation below. Later sections will relax this assumption by allowing for cross-sectional correlation, namely some aggregate risks. Further extensions are also allowed for cohort or time-specific volatility. The i.i.d. assumption implies at any time t, variance-covariance matrix of income shocks across individuals have is a diagonal matrix.

$$E(\epsilon_t'\epsilon_t|Y_{t-1}) = \sigma^2 I_n \quad \forall t \tag{5}$$

where σ^2 is the volatility of income shock and I_n is an identity matrix whose length is the number of agents in the economy, n. Although income volatility is not cohort-specific, any past shock still created different impacts on the young and old generations because their length of the proefessional career are different. This is reminiscent of Bansal and Yaron (2004). Since both ρ and σ^2 are not cohort-specific, I drop the subscript c from now on to avoid clustering.

Both ρ and σ are "true" parameters only known by the modeler, but unknown by agents in the economy. Individual i learns about the income process by "running" a regression based on the model above using a limited sample from her past experience starting from the year of entering the job market c up till t. Critically, for this paper's purpose, I allow the experience used for learning to include both her own and others' past income over the same period. It is admittedly bizarre to assume individual agents have access to the whole population's income. A more realistic assumption could be that only a small cross-sectional sample is available to the agent. Any scope of cross-sectional social learning suffices for the point to be made in this paper.

4.1.1 A baseline model of experience-based learning

If each agent knows *perfectly* the model parameters ρ and σ, the uncertainty about future income growth is

$$\begin{aligned} Var^*_{i,t}(\Delta y_{i,t+1}) &= Var^*_{i,t}(y_{i,t+1} - y_{i,t}) \\ &= Var^*_{i,t}((\rho - 1)y_{i,t} + \epsilon_{i,t+1}) \\ &= Var^*_{i,t}(\epsilon_{i,t+1}) \\ &= \sigma^2 \end{aligned} \tag{6}$$

The superscript $*$ is the notation for perfect understanding. The first equality follows because both $y_{i,t}$ and the persistent parameter ρ is known by the agent. The second follows because σ^2 is also known.

Under *imperfect* understanding and learning, both ρ and σ^2 are unknown to agents. Therefore, the agent needs to learn about the parameters from the small panel sample experienced up to that point of the time. We represent the sample estimates of ρ and σ^2 using $\widehat{\rho}$ and $\hat{\sigma}^2$.

$$\widehat{V}ar_{i,t}(\Delta y_{i,t+1}) = y^2_{i,t} \underbrace{\widehat{Var}^{\rho}_{i,t}}_{\text{Persistence uncertainty}} + \underbrace{\hat{\sigma}^2_{i,t}}_{\text{Shock uncertainty}} \tag{7}$$

The perceived risks of future income growth have two components. The first one comes from the uncertainty about the persistence parameter. It reflects how uncertain the agent feels about the degree to which realized income shocks will affect her future income, which is non-existent under perfect understanding. I will refer to this as the parameter uncertainty or persistence uncertainty hereafter. Notice the persistence uncertainty is scaled by the squared size of the contemporary income. It implies that the income risks are size-dependent under imperfect understanding. It introduces one of the possible channels via which current income affects perceived income risk.

The second component of perceived risk has to do with the unrealized shock itself. Therefore, it can be called shock uncertainty. Because the agent does not know perfectly the underlying volatility of the income shock, she makes an estimate based on past volatility. The estimates $\hat{\sigma}^2_{i,t}$ can be lower or higher than the true risks, but it is an unbiased estimator for the true σ^2.

We assume agents learn about the parameters using a least-square rule widely used in the learning literature (For instance, Evans and Honkapohja (2012), Malmendier and Nagel (2015)) The bounded rationality prevents her from adopting any more sophisticated rule that econometricians may consider to be superior to the OLS. (For instance, OLS applied in autocorrelated models induce bias in estimate.) We first consider the case when the agent understands that the income shocks are i.i.d. To put it differently, this is when the agent correctly specify the income model when learning. The least-square estimate of paramters are the following.

$$\hat{\rho}_{i,t} = (\sum_{k=0}^{t-c}\sum_{j=1}^{n} y^2_{j,t-k-1})^{-1}(\sum_{k=0}^{t-c}\sum_{j=1}^{n} y_{j,t-k-1}y_{j,t-k}) \tag{8}$$

The variance of sample residuls $\widehat{e}$ are used for estimating the income volatility σ^2. It can be seen as the experienced volatility over the past history.

$$\widehat{\sigma}^2_{i,t} = s^2_{i,t} = \frac{1}{N_{i,t}-1}\sum_{j=1}^{n}\sum_{k=0}^{t-c}\hat{e}^2_{j,t-k} \tag{9}$$

where $N_{i,t}$ is the size of the panel sample available to the agent i at time t. It is equal to $n(t-c)$, the number of people in the sample times the duration of agent i's career.

Under i.i.d. assumption, the estimated uncertainty about the estimate is

$$\widehat{Var}^{\rho}_{i,t} = (\sum_{k=0}^{t-c}\sum_{j=1}^{n} y^2_{j,t-k-1})^{-1}\widehat{\sigma}^2_{i,t} \tag{10}$$

Experience-based learning naturally introduces a mechanism for the perceived income risks to be cohort-specific and age-specific. Different generations who have experienced different realizations of the income shocks have different estimates of Var^{ρ} and σ^2, thus differ in their uncertainty about future income. In the meantime, people at an older age are faced with a larger sample size than younger ones, this will drive the age profile of perceived risks in line with the observation that the perceived risk is lower as one grows older. Also, note that the learning literature has explored a wide variety of assumptions on the gains from learning to decline over time or age. These features can be easily incorporated into my framework. For now, equal weighting of the past experience suffices for the exposition here.

We can rewrite the perceived risk under correct model specification as the following.

$$\widehat{Var}_{i,t}(\Delta y_{i,t+1}) = [(\sum_{k=0}^{t-c}\sum_{j=1}^{n} y^2_{j,t-k-1})^{-1}y^2_{i,t} + 1]\hat{\sigma}^2_{i,t} \tag{11}$$

4.1.2 Attribution

Attribution means that agents subjectively form perceptions about the correlation between their own income outcome and others. This opens room for possible model-misspecification about the nature of income shock due to bounded rationality. Although people specify the regression model correctly, they do not necessarily perceive the nature of the income shocks correctly.

Before introducing the specific mechanism of the attribution error, we can generally discuss the property of parameter uncertainty for any general subjective perception of the cross-sectional correlation. Under the least-square learning rule, the perceived uncertainty about the parameter estimate now takes a more general form as below. It is equivalent to accounting for within-time clustering in computing standard errors.

$$\tilde{Var}^{\rho}_{i,t} = (\sum_{k=0}^{t-c}\sum_{j=1}^{n} y^2_{j,t-k-1})^{-1}(\sum_{k=0}^{t-c}\tilde{\Omega}_{i,t-k})(\sum_{k=0}^{t-c}\sum_{j=1}^{n} y^2_{j,t-k-1})^{-1} \tag{12}$$

where $\tilde{\Omega}_{t-k}$ is the perceived variance-covariance of income and income shocks within each point of time. It reflect how individual i thinks about the correlation between her own income and others'.

$$\tilde{\Omega}_{i,t} = \tilde{E}_{i,t}(Y_{t-1}e'_t e_t Y_{t-1}) \tag{13}$$

If we assume constant group size n over time and the homoscedasticity, i.e. income risks σ do not change over time, given the individual ascribes a subjective correlation coefficient of $\tilde{\delta}_{\epsilon,i,t}$ across income shocks and a correlation $\tilde{\delta}_{y,i,t}$ across the levels of income, $\tilde{\Omega}_{i,t}$ can be approximated as the following. (See the appendix for derivation) (This is analogous to the cluster-robust standard error by Cameron et al. (2011). But the distinction is that both long-run and short-run correlation are subjective now.)

$$\tilde{\Omega}_t \approx \sum_{j=1}^{n} y^2_{j,t}(1+\tilde{\delta}_{y,i,t}\tilde{\delta}_{\epsilon,i,t}(n-1))\tilde{\sigma}^2_t \tag{14}$$

Therefore, the parameter uncertainty under the subjective attribution takes a following form comparable with that derive for i.i.d. in previous section.

$$\tilde{Var}^{\rho}_{i,t} = (\sum_{k=0}^{t-c}\sum_{j=1}^{n} y^2_{j,t-k-1})^{-1}(1+\tilde{\delta}_{i,t}(n-1))\tilde{\sigma}^2_t \tag{15}$$

Where we bundle the two correlation coefficients parameters together as a single parameter of the attribution correlation, which represents the degree of attribution errors.

$$\tilde{\delta}_{y,i,t}\tilde{\delta}_{\epsilon,i,t} \equiv \tilde{\delta}_{i,t} \tag{16}$$

The subjective attribution is jointly by two perceived correlation parameters, $\tilde{\delta}_{\epsilon}$ and $\tilde{\delta}_{y}$. They can be more intuively thought as long-run attribution and short-run attribution, respectively, because the former is the perceived correlation in the level of the income and later in income shocks. The multiplication of two jointly governs the degree to which the agents inflate experienced volatility in forming perceptions about future income risks. $\tilde{\delta}_{i,t}=0$ if the agent i thinks that her income shock or the long-run income is uncorrelated with others' ($\tilde{\delta}_{\epsilon}=0$ or $\tilde{\delta}_{y}=0$). In contrats, $\tilde{\delta}_{i,t}=1$, attaining its maximum value if the agent thinks both her income shock and income is perfectly correlated with others. In general, $\tilde{\delta}_{\epsilon,i,t}$ and $\tilde{\delta}_{y,i,t}$ are not necessarily consistent with the true income process. Since long-run correlation increases with the the short-run correlation, bundling them together as a single parameter is feasible.

Another important aspect regarding attribution is that it changes perceived risk only through its effect on parameter uncertainty but not on shock uncertainty. Attributing the individual outcome either to idiosyncrasy or common factors do not change how agents think of the variance of the shock, but changes the uncertainty about how persistent the effect of the shock will be. Therefore, for the attribution to play a meaningful role in perceived risk, the size of the income shock shall not be excessively so big that it overshadows the role of persistence uncertainty.

4.1.3 Attribution errors

The framework set up above can neatly incorporate the psychological tendency of ascribing bad luck to external causes and good luck to internal ones. The manifesto of the attribution error in this context is that people asymmetrically assign the subjective correlation $\tilde{\delta}_{i,t}$

depending on the sign of the recent income change (or the realized shocks). An internal attribution implies a positive change in income induces the agent to maintain the independence assumption, while an external attribution means a negative change in income makes the agent interpret the income shock as a common shock and thus positively correlated with others at each point of the time. More formally, we define the attribution error as the assymetric assignment of the value of $\tilde{\delta}_{i,t}$, specified as below.

$$\begin{aligned} \text{Internal attribution:} \quad & \tilde{\delta}_{i,t} = 0 \quad \text{if} \quad \Delta y_{i,t} > 0 \\ \text{External attribution:} \quad & \tilde{\delta}_{i,t} = 1 \quad \text{if} \quad \Delta y_{i,t} < 0 \end{aligned} \tag{17}$$

Here, I let the attribution be contingent on the income change $\Delta y_{i,t}$. An alternative way of modeling it is contingency on forecast errors, $\widehat{e}_{i,t}$, namely the unexpected income shock to agent i at time t. The distinction between the two modeling techniques is indistinguishable in terms of qualitative predictions I will discuss next.

One can immediately show the following the persistence uncertainty with external attribution is no smaller than that with internal attribution.

$$\tilde{Var}^{\rho}_{i,t} \geq \widehat{Var}^{\rho}_{i,t} \quad \forall \quad \tilde{\delta}_{i,t} \geq 0 \tag{18}$$

where the equality holds as a special case when $\tilde{\delta}_{i,t} = 0$. The left hand side monotonically increases with $\tilde{\delta}_{i,t}$.

In the meantime, the shock uncertainty estimate,σ^2 remain the same no matter if the attribution error arises, both of which are equal to the sample average of regression residuals s^2.

$$\tilde{\sigma}^2_{i,t} = \widehat{\sigma}^2_{i,t} \tag{19}$$

Combining the two relations above, one can show the perceived risks of an unlucky person is unambiguously higher than that of a lucky one.

$$\begin{aligned} \tilde{Var}_{i,t}(\Delta y_{i,t+1}) &= y^2_{i,t-1}\tilde{Var}^{\rho}_{i,t} + \tilde{\sigma}^2_{i,t} \\ &= [(\sum_{k=0}^{t-c}\sum_{j=1}^{n} y^2_{j,t-k-1})^{-1}(1+\tilde{\delta}_{i,t}(n-1))y^2_{i,t}+1]\tilde{\sigma}^2 \\ &\geq \widehat{Var}_{i,t}(\Delta y_{i,t+1}) \end{aligned} \tag{20}$$

where, again, the equality holds without attribution errors, i.e. $\tilde{\delta}_{i,t} = 0$. One way to rephrase the inequality above is that the unlucky group excessively extrapolates the realized shocks into her perception of risks. There is no distinction between the two groups if there is no attribution errors.

We have the following predictions about the perceived income risks from the analysis.

- Higher experienced volatility, measured by $s^2 \equiv \tilde{\sigma}^2_{i,t}$ leads to higher perceived income risks.

- In the same time, future perceptions of the risks inflate the past volatility by proportionately depending on their subjective attribution. A higher degree of external attribution reflected by a higher $\tilde{\delta}_{i,t}$ implies a higher inflaiton of past volatility into future. (See Figure 6.)

- With attribution errors, people project past experienced volatility into perceived risks disproportionately depending on the subjective attribution. A higher perceived attribution to common shocks, a bigger $\tilde{\delta}_{i,t}$ induces a higher perceived risk. See the comparison between Figure 7. This is different from the scenario without attribution errors.

It is important to note that this difference still arises even if one assumes the underlying shocks are indeed non-independent. Although different types of income shocks have different implications as to which group correctly or mis-specifies the model, it does not alter the distinction between the lucky and unlucky group. To put it bluntly, the underlying process determines who is over-confident or under-confident. But the lucky group is always more confident than the unlucky group.

4.1.4 Extrapolative attribution

The baseline model only lets the sign of the recent income change induce attribution errors, and assumes away the possibility of the attribution errors to depend on the magnitude of the recent changes endogenously. This is reflected in the model assumption that $\tilde{\delta}_i$ could take either 1 or 0 depending on the sign of the recent income change. We could alternatively allow the attributed correlation $\tilde{\delta}_i$ to be a function of the $\Delta(y_{i,t})$. This will open the room for income changes of different salience to induce different degrees of attribution errors.

In order to capture this size-dependent pattern, I choose an attribution function that takes the following form as the following. It does not have to be this function in particular, but its properties suit the purpose here.

$$\tilde{\delta}(\Delta y_{i,t}) = 1 - \frac{1}{(1 + e^{\alpha - \theta \Delta y_{i,t}})} \tag{21}$$

Basically, the attribution function is a variant of a logistic function with its function value bounded between $[0, 1]$. It takes an s-shape and the parameter θ governs the steepness of the s-shape around its input value. α is adjustable parameter chosen such that the attribution free of errors happen to be equal to the true correlation between individuals δ, which here takes values of zero for independence assumption. In the model, θ is the parameter that governs the degree of the attribution errors. It takes any non-negative value. Although the qualitative pattern induced by the attribution errors stands for any positive θ, letting it be a parameter leaves modelers the room to recover it from subjective risks data. The attribution function under different θ is shown in Figure 8. The higher θ is, the more sensitive the assigned correlation is to the size of the shock, thus inducing a higher dispersion of the perceived correlation between the lucky group and the unlucky group.

4.2 Simulation

4.2.1 Current income and perceived risks

How do perceived risks depend on the current income level of $y_{i,t}$? Since the recent income changes $\Delta y_{i,t}$ triggers asymmetric attribution, the perceived risks depend on the current level of income beyond the past-dependence of future income on current income that is embodied in the AR(1) process. In particular, $\widehat{Var}^{\rho}_{i,t}$ does not depend on $\Delta y_{i,t}$ while $\tilde{Var}^{\rho}_{i,t}$ does and is always greater than the former as a positive, it will amplify the loading of the current level of income into perceived risks about future income. This generates a U-shaped perceived income profile depending on current level income.

Figure 9 and 10 plots both the theory-predicted and simulated correlation between $y_{i,t}$ and perceived income risks with/without attribution errors. In the former scenario, perceived risks only mildly change with current income and the entire income profile of perceived risk is approximately flat. In the latter scenario, in contrast, perceived risks exhibit a clear U-shape across the income distribution. People sitting at both ends of the income distribution have high perceived risks than ones in the middle. The non-monotonic of the income profile arise due to the combined effects directly from $y_{i,t}$ and indirectly via its impact on $\tilde{Var}^{\rho}$. The former effect is symmetric around the long-run average of income (zero here). Deviations from the long-run mean on both sides lead to higher perceived risk. The latter monotonically decreases with current income because higher income level is associated with a more positive income change recently. The two effects combined create a U-shaped pattern.

A subtle but interesting point is that the U-shape is skewed toward left, meaning perceived risks decrease with the income over the most part of the income distribution before the pattern reverses. More intuitively, it means that although low and high income perceived risks to be higher because of its deviation from the its long-run mean. This force is muted for the high income group because they have a lower peceived risks due to the attribution errors.

4.2.2 Age and experience and perceived risks

4.2.3 Aggregate risk

Previously, I assume the underlying shock is i.i.d. This section considers the implication of the attribution errors in the presence of both aggregate and idiosyncratic risks. This can be modeled by assuming that the shocks to individuals' income are positively correlated with each other at each point of the time. Denoting $\delta > 0$ as the true cross-sectional correlation of income shocks, the conditional variance-covariance of income shocks within each period is the following.

$$E(\epsilon_t'\epsilon_t|Y_{t-1}) = \Sigma^2 = \sigma^2\Omega \quad \forall t \tag{22}$$

where Ω takes one in its diagonal and δ in off-diagonal.

The learning process and the attribution errors all stay the same as before. Individuals specify their subjective structure of the shocks depending on the sign and size of their own experienced income changes. By the same mechanism elaborated above, a lucky person has lower perceived risks than her unlucky peer at any point of the time. This distinction between the two group stays the same even if the underlying income shocks are indeed correlated.

What's new in the presence of aggregate risks lies in the behaviors of average perceived risks, because there is an aggregate shock that drives the comovement of the income shocks affecting individuals. Compared to the environment with pure idiosyncratic risks, there is no longer an approximately equal fraction of lucky and unlucky agents at a given time. Instead, the relative fraction of each group depends on the recently realized aggregate shock. If the aggregate shock is positive, more people have experienced good luck and may, therefore, underestimate the correlation (a smaller $\tilde{\delta}$). This drives down the average perceived income risks among the population. If the aggregate shock is negative, more people have just experienced income decrease thus arriving at a higher perceived income uncertainty.

This naturally leads to a counter-cyclical pattern of the average perceived risks in the economy. The interplay of aggregate risks and attribution errors adds cyclical movements of the average perceived risks. The two conditions are both necessary to generate this pattern. Without the aggregate risk, both income shocks and perceived income shocks are purely idiosyncratic and they are averaged out in the aggregate level. Without attribution errors, agents symmetrically process experiences when forming future risk perceptions.

Figure 12 illustrates the first point. The scatter plots showcase the correlation between average income changes across population and average perceive risks under purely idiosyncratic risks and aggregate risks. The negative correlation with aggregate risks illustrate the counter-cylical perceived risks. There is no such a correlation under purely idiosyncratic risks. Figure **??** testifies the second point. It plots the same correlation with and without attribution errors when the aggregate risk exists. Attribution errors brings about the asymmetry not seen when the bias is absent.

5 Coclusion

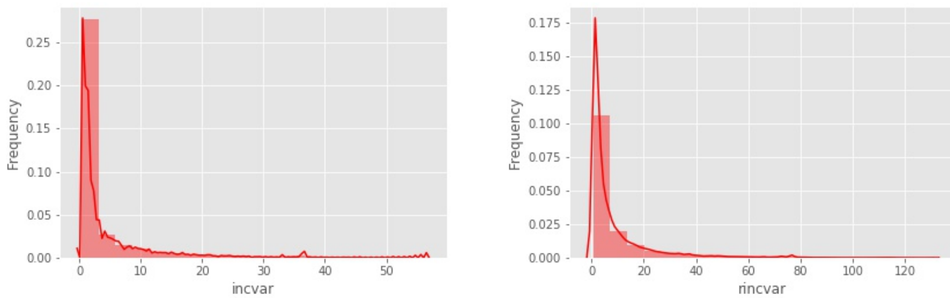
How do people form perceptions about their income risks? Theoretically, this paper builds an experience-based learning model that features an imperfect understanding of the size of the risks as well as its nature. By extending the learning-from-experience into a cross-sectional setting, I introduce a mechanism in which future risk perceptions are dependent upon past income volatility or cross-sectional distributions of the income shocks. I also introduce a novel channel - subjective attribution, into the learning to capture how income risk perceptions are also affected by the subjective determination of the nature of income risks. It is shown that the model generates a few testable predictions about the relationship between experience/age/income and perceived income risks.

Empirically, I utilize recently available panel of income density surveys of U.S. earners to shed light directly on a subjective income risk profiles. I explore the cross-sectional heterogeneity in income risk perceptions across ages, generations, and income group as well as its cyclicality with the current labor market outcome. I found that risk perceptions are positively correlated with experienced income volatility, therefore differing across age and cohorts. I also found perceived income risks of earners counter-cyclically react to the recent labor market conditions.

As a next step, the project will build the experience-based-learning based on subjective attribution model into an otherwise life cycle model of consumption/saving.

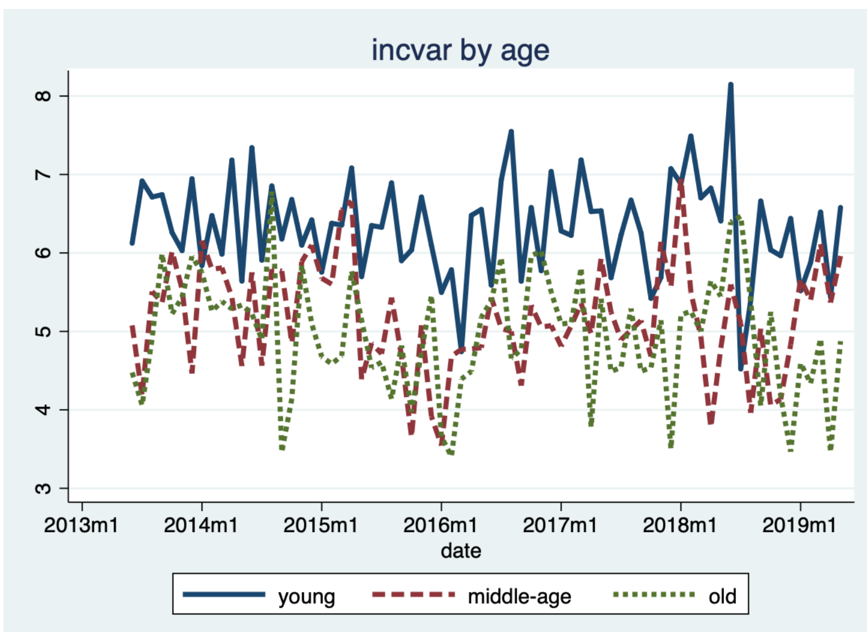
Tables and Figures

Figure 1: Distribution of Individual Moments



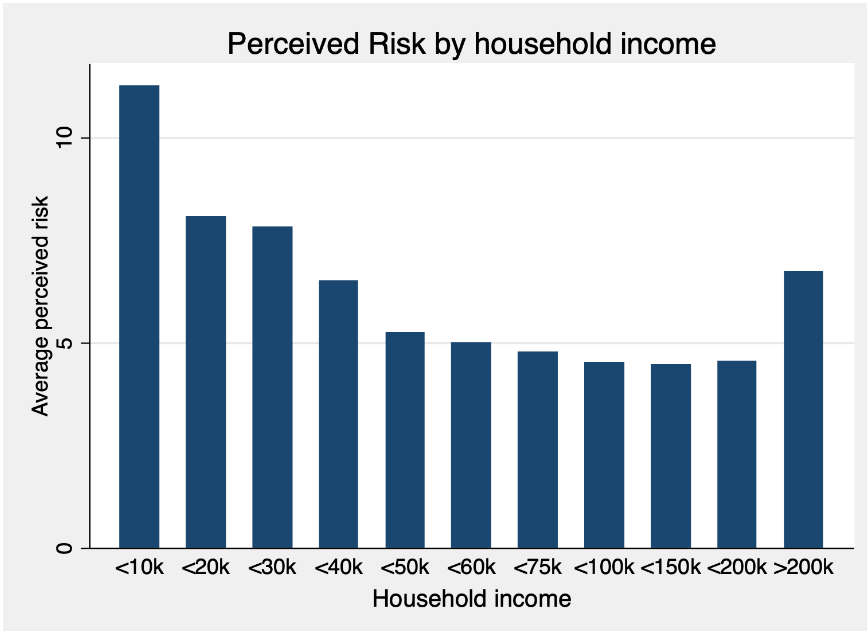
Note: this figure plots the perceived risks of nominal and real income.

Figure 2: Perceived Income by Age



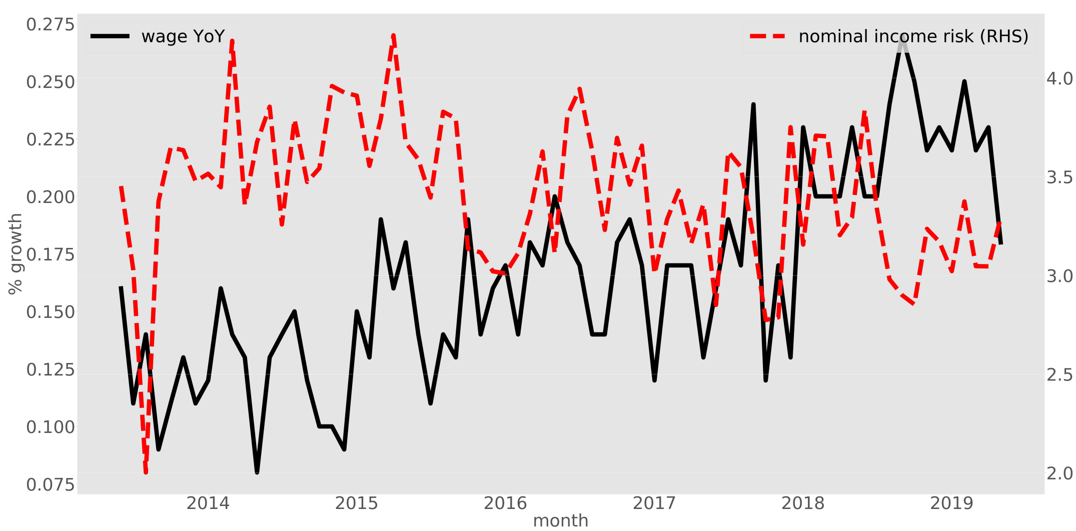
Note: this figure plots average perceived income risks of different age groups over time.

Figure 3: Perceived Income by Income



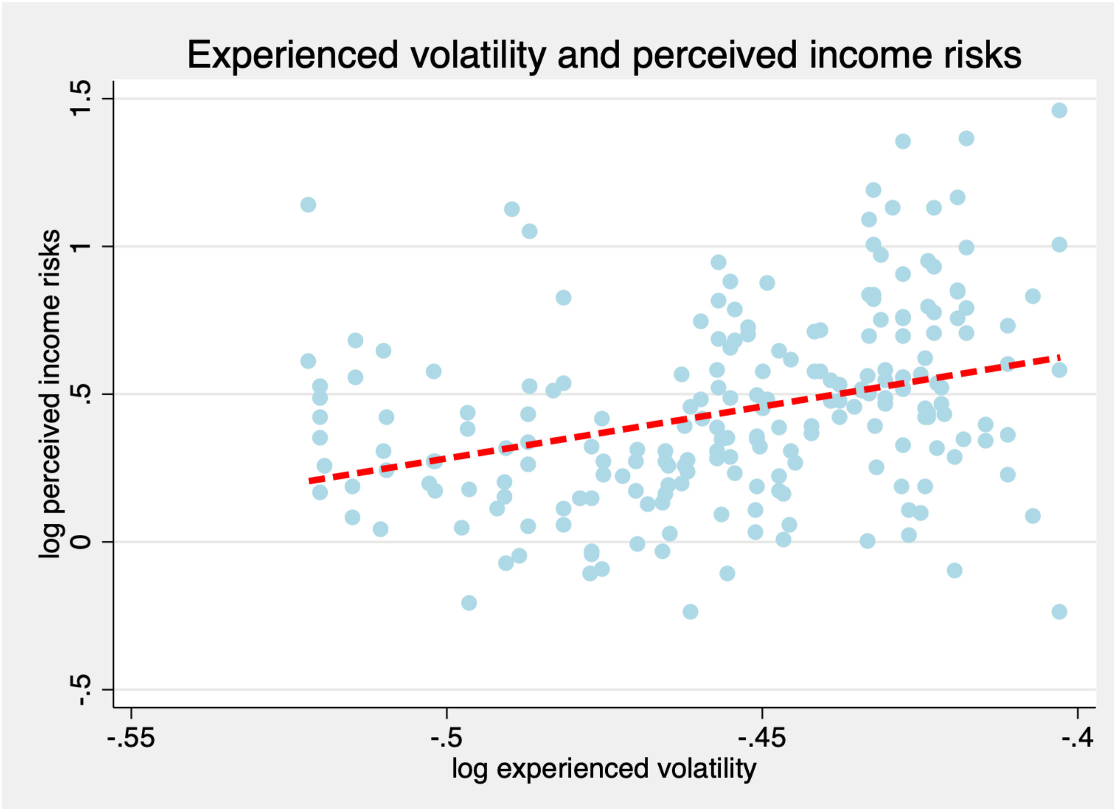
Note: this figure plots average perceived income risks by the range of household income.

Figure 4: Recent Labor Market Outcome and Perceived Risks



Note: recent labor market outcome is measured by hourly earning growth (YoY).

Figure 5: Experienced Volatility and Perceived Income Risk



Note: experienced volatility is the mean squred error(MSE) of income regression based on a particular year-cohort sample. The perceived income risk is the average across all individuals from the cohort in that year.

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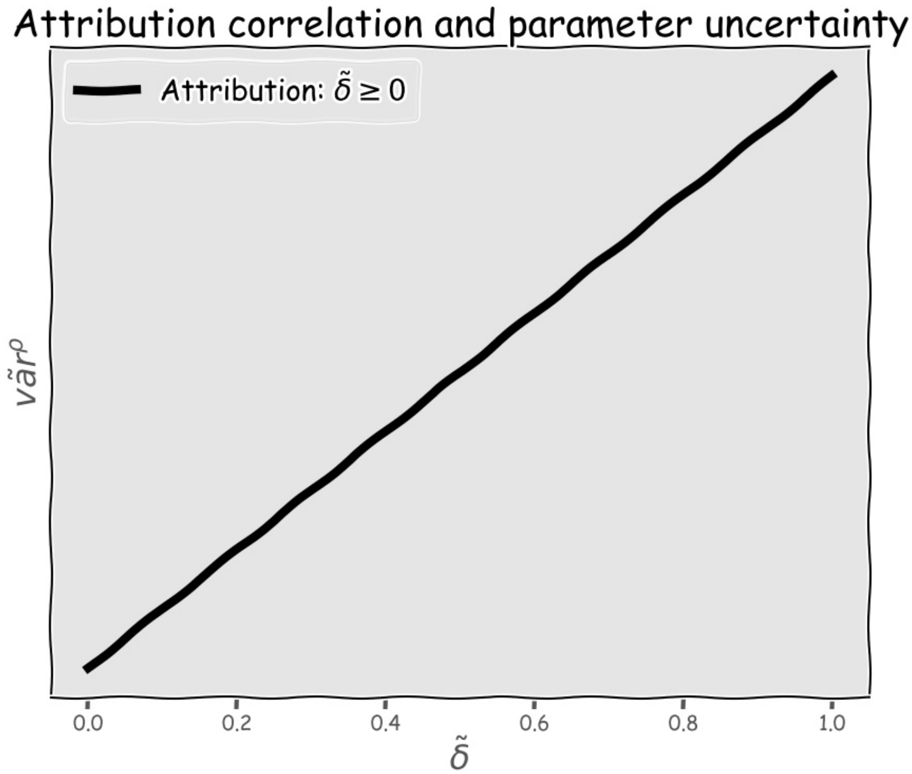
Figure 6: Attribution and Parameter Uncertainty



Note: this figure illustrates how parameter uncertainty changes with the subjective correlation of one's own income and others'.

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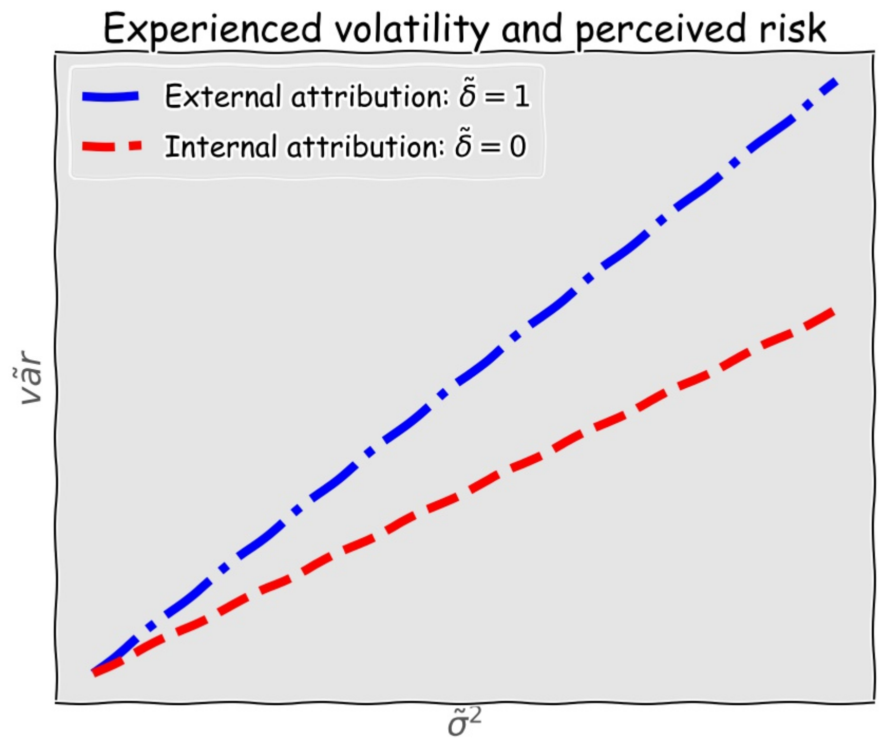
Figure 7: Experienced Volatility and Perceived Risk



Note: this figure illustrates the relationship between experienced volatility and perceived income income risk under different attributions.

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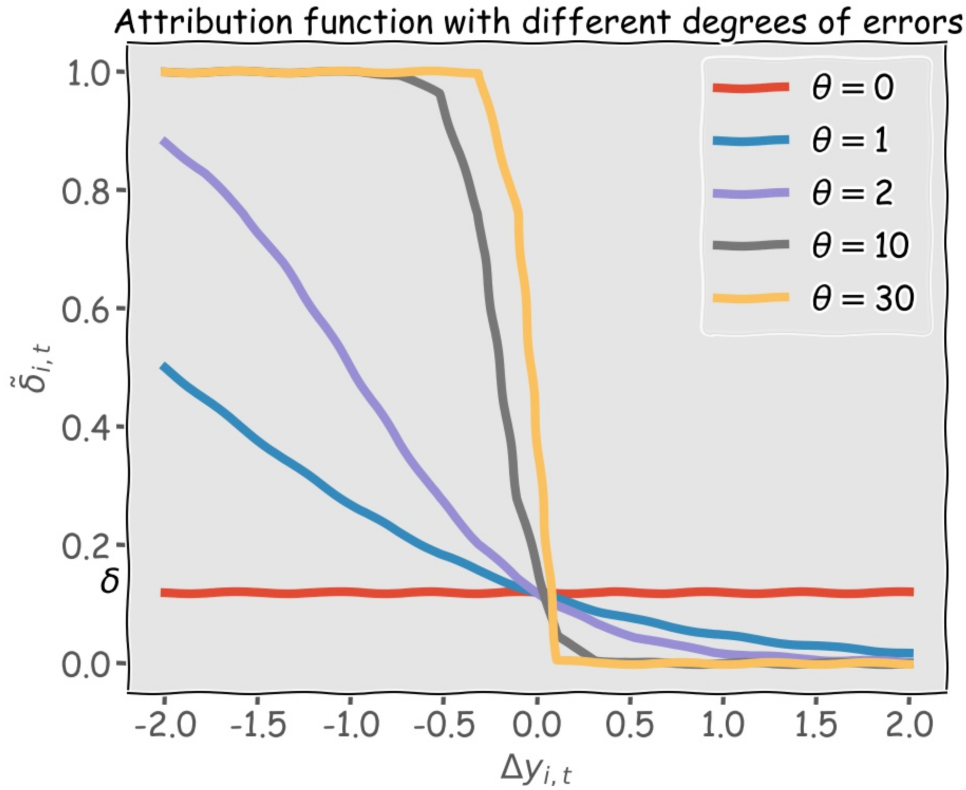
Figure 8: Attribution Function



Note: this figure illustrates the parameterized attribution function under different degree of attribution error governed by θ.

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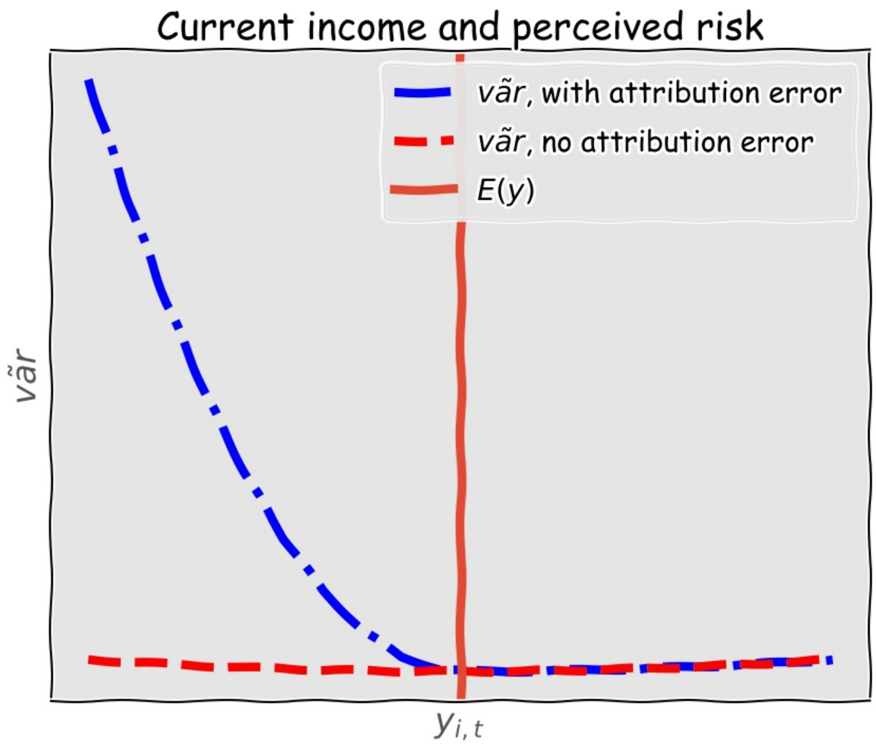
Figure 9: Current Income and Perceived Risk



Note: this figure plots the theoretical prediction of the relationship between current income and perceived income risks.

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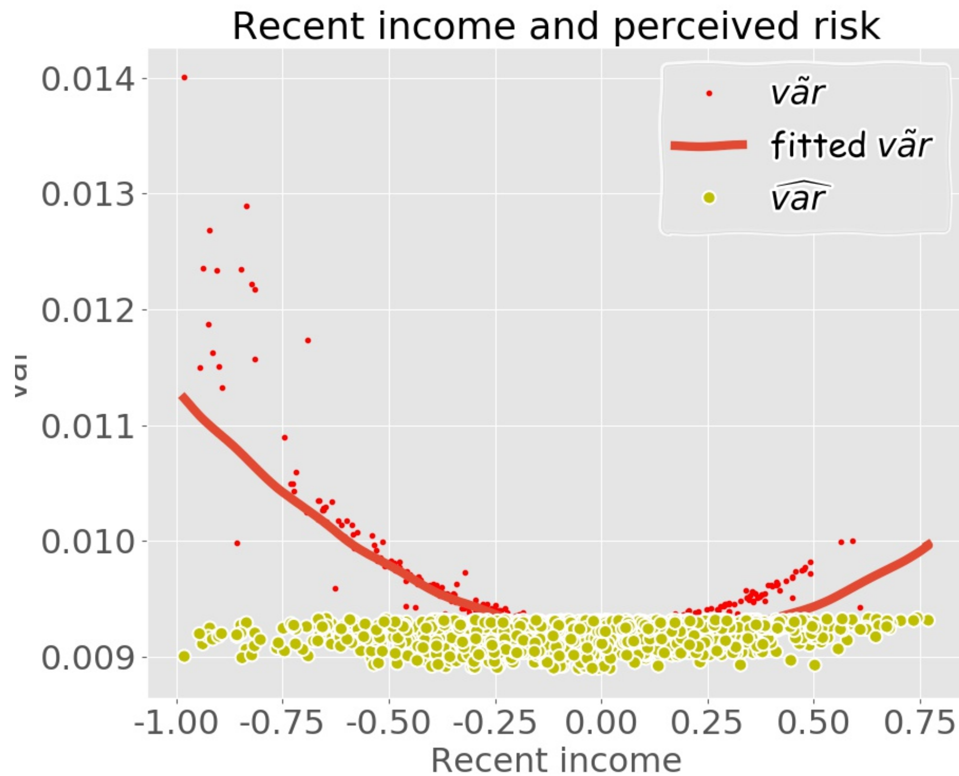
Figure 10: Simulated Income Profile of Perceived Risk



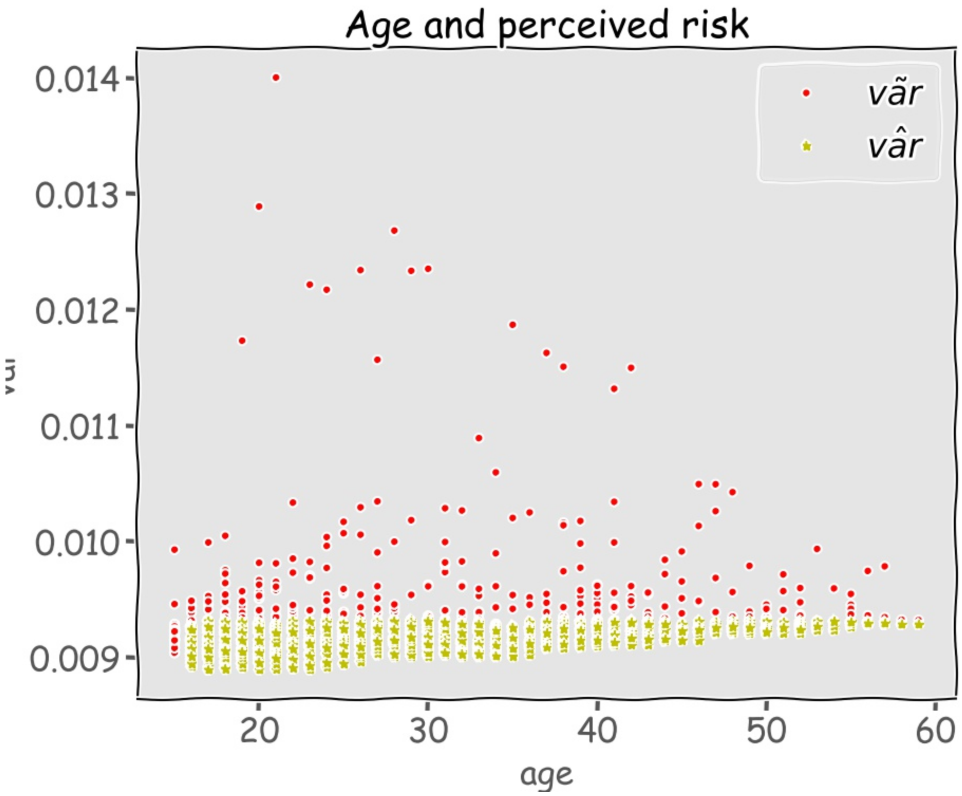
Note: this figure plots the simulated relationship between current income and perceived income risks under the theory.

Table 1: Current Labor Market Conditions and Perceived Income Risks

	mean:var	mean:iqr	mean:rvar	median:var	median:iqr	median:rvar
0	-0.24**	-0.36***	-0.47***	-0.15	-0.15	-0.53***
1	-0.44***	-0.53***	-0.56***	-0.01	0.01	-0.55***
2	-0.37***	-0.42***	-0.43***	-0.09	-0.07	-0.45***
3	-0.4***	-0.43***	-0.41***	-0.09	-0.09	-0.46***
4	-0.28**	-0.38***	-0.31**	-0.27**	-0.24*	-0.49***

*** 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 $t, t-1, ..., t-k$.

Figure 11: Simulated Age Profile of Perceived Risk



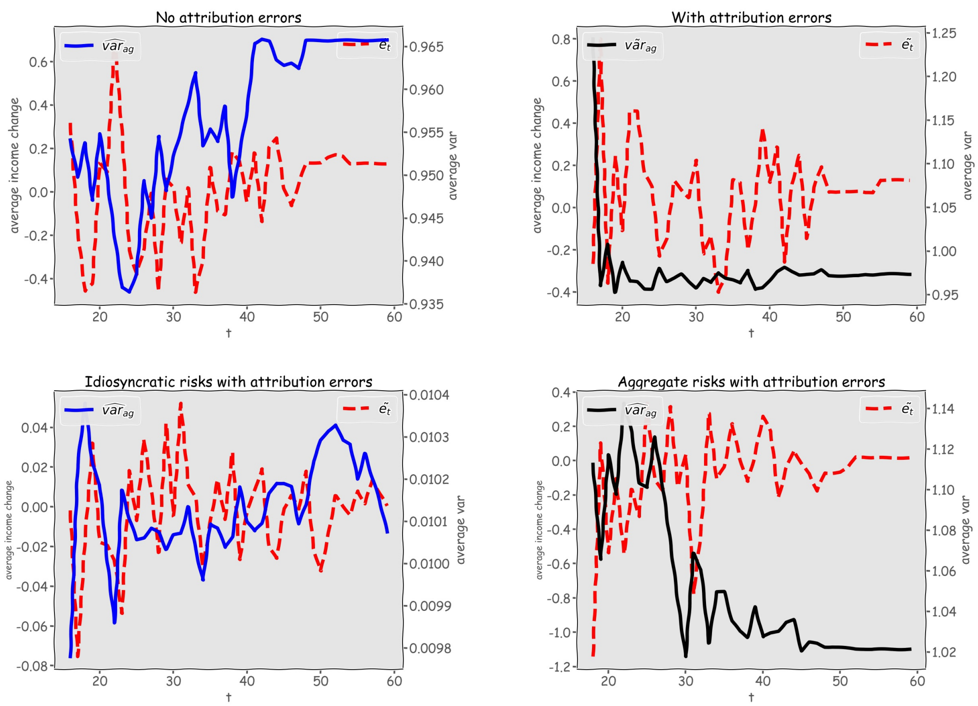
Note: this figure plots the simulated relationship between age and perceived income risks.

Table 2: Average Perceived Risks and State Labor Market

	(1)	(2)	(3)	(4)
	log(var)	log(risk)	log(iqr)	log(iqr)
wage growth	-0.05***		-0.03***	
	(0.01)		(0.01)	
unemp rate		0.04*		0.04***
		(0.02)		(0.01)
Observations	3529	3529	3546	3546
R-squared	0.023	0.020	0.025	0.028

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

Figure 12: Simulatd Average Labor Market and Perceived Risk



Note: this figure plots the simulated relationship between average perceived risks and average income changes with/without attribution errors (the upper panel) and under aggregate/idiosyncratic risks (the bottom panel).

Table 3: Perceived Income Risks, Experienced Volatility and Individual Characteristics

	incvar I	incvar II	incvar III	incvar IIII	incvar IIIII
expvol	6.31***	2.92***	3.56***	3.56***	6.15***
	(0.40)	(0.83)	(0.91)	(0.91)	(0.92)
age_gr=30-39		-0.33***	-0.34***	-0.34***	-0.38***
		(0.03)	(0.03)	(0.03)	(0.03)
age_gr=40-48		-0.51***	-0.53***	-0.53***	-0.61***
		(0.03)	(0.03)	(0.03)	(0.03)
age_gr=49-57		-0.61***	-0.59***	-0.59***	-0.65***
		(0.03)	(0.03)	(0.03)	(0.03)
age_gr=>57		-0.48***	-0.48***	-0.48***	-0.58***
		(0.04)	(0.05)	(0.05)	(0.05)
HHinc_gr=low inc			0.20***	0.20***	0.15***
			(0.02)	(0.02)	(0.02)
educ_gr=low educ			-0.11***	-0.11***	-0.08***
			(0.02)	(0.02)	(0.02)
gender=male			-0.38***	-0.38***	-0.31***
			(0.02)	(0.02)	(0.02)
parttime=yes					-0.03
					(0.02)
selfemp=yes					0.00***
					(0.00)
UEprobAgg					0.00***
					(0.00)
UEprobInd					0.00***
					(0.00)
N	40529	40529	34101	34101	28898
R2	0.01	0.02	0.04	0.04	0.05

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

This table reports results associated a regression of looged perceived income risks (incvar) on logged experienced volatility (expvol) and a list of household specific variables such as age, income, education, gender, job type and unemployment expectations.

Table 4: Perceived Income Risks and Household Spending

	spending I	spending II	spending III	spending IIII	spending IIIII
incexp	0.39***				
	(0.08)				
incvar		0.58***			
		(0.13)			
rincvar			1.08***		
			(0.15)		
incskew				0.19	
				(0.45)	
UEprobAgg					0.44*
					(0.25)
N	53455	53171	49986	52751	76531
R2	0.00	0.00	0.00	0.00	0.00

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).