Perceived Income Risks

Tao Wang

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Abstract

Heterogenous-agent models typically assume a perfect understanding of the size and nature of income risks. This paper explores the implications of imperfect understanding. I first document the following empirical patterns of subjective income profile utilizing a density survey. First, earners who are younger, from younger generations and from low-income households have higher perceived risks. Second, perceptions of risks countercyclically react to recent realizations of labor market outcomes. Third, there is a skewed U-shaped correlation between individual risk perceptions and current income. 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 U-shaped income-profile of risk perceptions and its countercyclical dynamics.

1 Introduction

"The devil is in higher moments." Even if two people share identical expected income and homogeneous preferences, different degrees of income risks still lead to starkly different decisions such as saving/consumption and portfolio choices. This is well understood in models in which agents are inter-temporally risk-averse, or prudent, and the risks associated with future marginal utility motivate precautionary motives. The same logic carries through to models in which capital income and portfolio returns are stochastic, and the risks of returns naturally become the center of asset pricing. Such behavioral regularities equipped with market incompleteness due to reasons such as imperfect insurance and credit constraints have also been the cornerstone assumptions used in the literature on heterogeneous-agent macroeconomics.

Economists have long utilized cross-sectional distributions of realized microdata to estimate the stochastic environments relevant to the agents' decision, such as the income process. And then in modeling the estimated risk profile is taken as parametric inputs and the individual shocks are simply drawn from the shared distributions. (See Blundell et al. (2008) as an example.) But one assumption implicitly made when doing this is that the agents in the model perfectly understand thus agree on the income risk profile imposed on them.

As shown by the actively developing literature on expectation formation, in particular, the mounting evidence on 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.

This paper's goal is to understand the question discussed above by directly shedding light on the subjective income profile using 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. It is at a monthly frequency and has a panel structure allowing for consecutive observations of the same household over a horizon of 12 months. 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.

Empirically, I can immediately ask the following questions.

- How much heterogeneity is there across workers' perceived income risks? What factors, i.e. household income, demographics, and other expectations, are correlated with the subjective risks in both individual and macro level?
- To what extent this heterogeneity in perceptions align with the true income risks facing different population group, or at least partly attributed to perceptive differences due to heterogeneity in information and information processing, as discussed in many models of expectation formation?
  - If we treat the income risks identified from cross-sectional inequality by econometricians as a benchmark, to what extent are the risks perceived by the agents?
    * If agents know more than econometricians about their individual earnings, should the perceived risks be lower than the econometrician's estimates?
    * Or actually, do agents, due to inattention or other information rigidity in learning about recently realized shocks, perceive the overall risk to be higher?
- If the subjective income risk can be decomposed into components of varying persistence (i.e. permanent vs transitory) based on assumed income process, it is possible to characterize potential deviations of perceptive income process from some well defined rational benchmark.
  - For instance, if agents overestimate their permanent income risks?
  - If agents overestimate the persistence of the income process? Rozsypal and Schlafmann (2017)

- One step back, if the log-normality assumption of income progress consistent with the surveyed data. Or it has non-zero skewness? This can be jointly tested using higher moments of the density forecasts.

- Finally, not just the process of earning itself, but also its covariance with macro-environment, risky asset returns, matter a great deal. For instance, if perceived income risks are counter-cyclical, it has important labor supply and portfolio implications. (Guvenen et al. (2014), Catherine (2019))

One of the key challenges when addressing these questions is to separately account for the differences in perceived risks driven by differences in underlying risk profiles, i.e. the "truth", and the rest driven by perceptive and informational heterogeneity. The most straightforward way seems to be to compare econometrician's external estimates of the income process using realized data and the perceived from the subjective survey. But this approach implicitly assumes that econometricians correctly specify the model of the income process and ignores the likely superior information problem discussed above. Therefore, in this paper, instead of simply assuming the external estimate by econometricians is the true underlying income process, I characterize the differences between perception and the true process by jointly recovering the process using realized data and expectations based on a particular well-defined theory of expectation formation. The advantage of doing this is that one does not need to make a stringent assumption about either agents' full rationality or econometricians' correctness of model specification. It allows econometricians to utilize the information from expectations to understand the true law of the system. This is in a similar spirit to Guvenen and Smith (2014), although the author does not use expectation survey but the consumption choice as the additional input for the joint estimation.

Theoretically, once I can document robustly some patterns of the perceived income risks profile, it can ben incorporated into an otherwise standard life-cycle model involving consumption/portfolio decisions to explore its macro implications. Ex-ante, one may conjecture a few of the following scenarios.

- If the subjective risks or skewness is found to be negatively correlated with the risky market return or business cycles, this exposes agents to more risks than a non-state-dependent income profile.

- If according to the subjective risk profile, the downside risks are highly persistent than typically assumed, then it is in line with the rare disaster idea.

- The perceptual differences lead to differences in MPCs, which is a different mechanism from credit-constraints and non-insurance of risks.

1.1 Relevant literature and potential contribution

This paper is relevant to four lines of literature. First, 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 **??**.

Second, this paper is inspired by 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' perceptive imperfection. The novelty of my paper lies in the primary focus on the implications of heterogeneity in perceived higher moments such as risks and skewness. 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.

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.

Lastly, 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.

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 2018, in total of 60 months. This makes about 79000 household-year observations, among which around 53,000 observations provide non-empty answers to the density question on earning growth.

Particular 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 percent 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 same location has two important implications for my analysis. First, the 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, risks and tail risks measured here are only conditional. 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, it does not fully reflect the labor income risk profile relevant to each individual.

In so far as we want to tease out the earning changes from voluntary decisions, moving to a different job position should actually not be included in earning expectations. Therefore only the exclusion of an unemployment scenario is relevant for my purpose in characterizing the labor income risks. But what is assuring me 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 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 will be fitted with a generalized beta distribution. In particular, if there is no open-ended bin on the left or right, then 2-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 4-parameter beta distribution is estimated. In the second case, in which there are exactly 2 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.

I have a reason to discuss at length the exact procedures for density distribution. It is important for this paper's purpose because I need 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 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. For those of you who may wonder, the fractions of the density answers fitted with the beta, uniform, and triangular distributions are, respectively, xxx, xxx, xxx in our sample.

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 numeric estimation program. Therefore, for each moment of the analysis, I exclude top and bottom 5% observations, leading to a sample size of around 45,000.

I also recognize what is really relevant to many economic decisions such as consumption is real income instead of nominal income. Thanks to the availability of inflation expectation and inflation uncertainty (also estimated from density question) can be used to convert nominal earning growth moments to real terms. 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.

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

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 36,000.

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 below, I plot the histograms of $\overline{\Delta} y_{i,t}$, $\overline{var}_{i,t}$, $\overline{skw}_{i,t}$, $\overline{\Delta y^r}_{i,t}$, $\overline{var^r}_{i,t}$.

First, expected income growth across the population exhibits a dispersion ranging from a decrease of $2-3\%$ to around an increase of 10% in nominal terms. Given the well-known downward wage rigidity, it is not surprising that most of the people expect a positive earning growth. At the same time, the distribution of expected income growth is right-skewed, meaning that more workers expect a smaller than larger wage growth. What is interesting is that this cross-sectional right-skewness in nominal earning disappears in expected real terms. Expected earnings growth adjusted by individual inflation expectation becomes symmetric around zero, ranging from a decrease of 10% to an increase of 10%. Real labor income increase and decrease are approximately equally likely.

Second, as the primary focus of this paper, perceived income risks also have a notable cross-sectional dispersion. For both measures of risks variance and iqr, and in terms of 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 earning growth of 2.4%, and a perceived risk of 1% standard deviation. This implies by no means negligible earning risk.

Third, the subjective skewness, an indicator of symmetry of the perceived density or upper/lower tail risk, are distributed across populations symmetrically around zero. It ranges from a left-skewness or negative skewness of 0.6 to the same size of positive skewness or right-skewness. Although one may think, based on the general knowledge of the cross-sectional distribution of the earnings growth, a right-skewness is more common, it turns out that approximately equal proportion of the sample has left and right tails of their individual earning growth expectation. It is important to note here that this pattern is not particularly due to our density estimation assumptions. Both uniform and isosceles triangular distribution deliver a skewness of zero. (This is also why we can observe a clear cluster of the skewness at zero.) Therefore, the non-zero skewness estimates in our sample are both from the beta distribution cases, which is flexible enough to allow both.

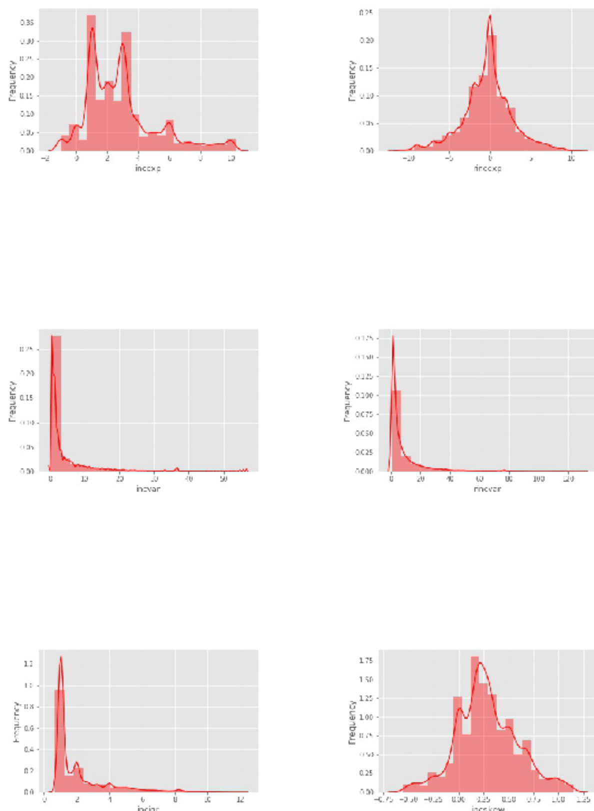

Figure 1: Distribution of Individual Moments

3.2 Correlation with past labor market outcome

This section shows that the perceived income risks are countercylical, i.e. perceived risks are negatively correlated with the recent labor market outcomes.

3.3 Correlation with asset returns

It is not only the labor income risk profile per se but also the macro risk profile, i.e. how the labor income is correlated with risky asset return and the business cycle, that is important for household decisions. Since the short time period of my sample (2013M6-2018M5) has not seen a single one business cycle, at least as defined by the NBER recession committee, it poses

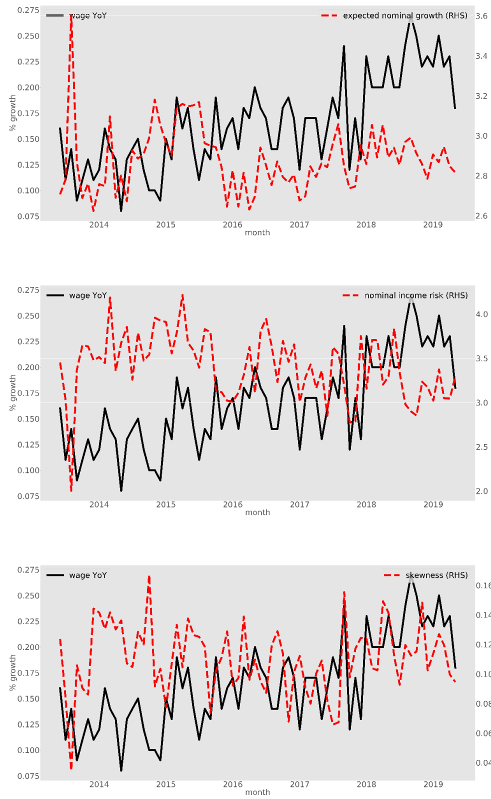

Figure 2: Recent Labor Market Outcome and Perceived Risks

a challenge for me to examine the correlation between perceived risks and macroeconomic cycles. Therefore, as the first stage of the analysis, I only focus on the correlation between perceived risks and stock market returns.

Of course, there is a rationale in the first place to study stock market return and labor income, as it bears critical implications for household consumption insurance, equity premium, and participation puzzle. For instance, a negative correlation of income risk and risky asset return means households will be faced with higher risks of their total income by investing in the stock market. Or a negative correlation between skewness and stock market return, meaning a bigger income increase is less likely in low-return times will also deter households from participating in the stock market.

Following the most common practice in the finance literature, I use the monthly return of the S&P 500, computed from the beginning to the end of the month, as an approximate of the stock market return. Over the sample period, there are exactly two-thirds of the time marking a positive return.

For a population summary statistic of individual moments of perceived income growth, I take the median and mean across all respondents in the survey for each point of the time. One may worry about the seasonality of the monthly series of this kind. For instance, it is possible that workers tend to learn news about their future earnings at a particular month of the year, i.e. end of the fiscal year when the wage contracts are renegotiated and updated.

Reasons of this kind may result in seasonal patterns of the expected earning growth, variance and other moments. Because my time series is too short in sample size to perform a trustful seasonal adjustment, I check the seasonality by inspecting the auto-correlation of each time series at different lags. As seen in the figures in the appendix, although it seems that the average or median earning growth per se has some seasonal patterns, there is no evidence for higher moments, such as variance and skewness.

There are two crucial econometric considerations when we examine the correlation between the subjective moments of earning growth and stock return.

The first is the time-average or time-aggregation problem documented in both empirical asset pricing and consumption insurance literature (Working (1960), Jagannathan and Wang (2007), Crawley (2019)). Variables such as consumption and earning are interval measures, reported as an average over a period, while the stock return is a spot measure computed between two points of the time. As a result, if the unit of the time for the underlying income process is at a higher frequency than the measured interval (an extreme case being the continuous-time), the measured variable will exhibit upward biased autocorrelation and correlation with other underlying random walk series in the same frequency. In my context, such a problem can be partly mitigated by the availability of monthly frequency of earning expectations, if we assume the unit of time of the underlying stochastic process is a month. Then the directly observed monthly correlation of the two cannot be driven by the time aggregation problem. What also becomes immediately clear from this consideration is that I should not examine the correlation of the two series in moving average terms, because it will cause the time aggregation problem. This point will be discussed in greater detail in the next section when I decompose the perceived income risks to different components of varying persistence.

The second issue regards which of the following, lagged, contemporaneous or forward is the correct correlation one should look at. Considering what is relevant to an individual making decisions are unrealized stochastic shocks to both income and asset return, one should examine the 1-year-ahead earning growth and its risks with the realized return over the impeding 12 months at each point of the time.

With these considerations, in the Figure 3, I plot the median perceived risk and skewness of both nominal and real earning along with the contemporaneous stock market returns by the end of each month (also true for the mean, see Figure 2 in appendix.). In order to account for the fact that the survey is undertaken in the middle of the month while the return is computed at the end of the month, I take the lag the income moments by 1 or 2 months when calculating the correlation coefficient. Table 4 reports correlation coefficients of between perceived risks and the realized stock market return over the next 0-6 months. Although a Pearson test of the correlation coefficients is only significant for a 2-month lag, overall, the income risks measured by variance and IQR for both nominal and real earning post a negative correlation with the realized stock return a few months ahead. The subjective skewness has also a negative associated with the realized stock return in the near future.

More caution is needed when interpreting the observed negative association between perceived earning risks/skewness with stock market returns. First, my sample period is short and has mostly posted positive returns. Second, the pattern is based on a population median and mean of the perceived income risks, and it does not account for any household-specific characteristics. As we have seen in the cross-sectional pattern, there are substantial variations across individuals in their perceived income risks and skewness. Third, the risk profile we consider here is only relevant for marginal consumers/investors who at least have access to the stock market in the first place. Therefore, it is worth exploring the correlation above conditional on more individual characteristics.

3.4 Role of individual characteristics

What factors are associated with subjective riskiness of labor income? This section inspects the question by regressing the perceived income risks at individual level on three major blocks of variables: job-specific characteristics, household demographics and other macroeconomic expectations held by the respondent.

In a general form, the regression is specified as followed, where the dependent variable is one of the individual subjective moments that represent perceived income risks for either nominal or real earning.

$$\{\overline{var}_{i,t}, \overline{var}^{r}_{i,t}, \overline{iqr}_{i,t}\} = \alpha + \beta_0 \text{HH}_{i,t} + \beta_1 \text{JobType}_{i,t} + \beta_2 \text{Exp}_{i,t} + \beta_3 \text{Month}_t + \epsilon_{i,t} \tag{3}$$

The first 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. Since the earning growth is specifically asked regarding the current job of the individual, I can directly test if a part-time job and the self-employed job is associated with higher perceived risks.

The second type of factors denoted $HH_{i,t}$ represents household-specific demographics such as the 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, the probability of stock market rise over the next year and the probability of a higher nationwide unemployment rate.

$Month_t$ is meant to control possible seasonal or month-of-the-year fixed effects. It may well be the case that at a certain point of the time of the year, workers are more likely to learn about news to their future earnings. But as I have shown in the previous section, such evidence is limited particularly for the higher moments of earnings growth expectations.

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 are presented in Table 3 below for three measures of perceived income risks, nominal growth variance, nominal growth IQR, and real growth variance.

The regression results are rather intuitive. It confirms that self-employed jobs, workers from low-income households and lower education 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. In the Table **??** shown in the appendix, this group of people also has higher expected earnings growth. 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.

The negative correlation between perceived risks and household income is significant and robust throughout all specifications. In contrast, there is no such correlation between expected earning growth per se and household income. Although SCE asks the respondent to report an income range instead of the accurate monetary value, the 11-group breakdown is sufficiently granular to examine if the high-income/low risks association is monotonic. As implied by the size of the coefficient of each income group dummy in the Table 3, this pattern is monotonically negative until the top income group ($200k or above). I also plot the mean and median of income risks by income group in the Figure 4.

Besides household income, there is also a statistical correlation between perceived risks and other demographic variables. In particular, higher education, being a male versus female, being a middle-aged worker compared to a young, are all associated with lower perceived income risks. To keep a sufficiently large sample size, I run regressions of this set of variables without controlling the rest regressors. Although the sample size shrinks substantially by including these demographics, the relationships are statistically significant and consistent across all measures of earning risks.

Higher perceived the probability of losing the current job, which I call individual unemployment risk, $IndUE$ 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, $AggUE$ 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.

Lastly, what is ambiguous from the regression is the correlation between stock market expectations and perceived income risks. Although a more positive stock market expectation is associated with higher expected earnings growth in both real and nominal terms, it is positively correlated with nominal earning risks but negatively correlated with real earning risks. As the real earning risk is the summation of the perceived risk of nominal earning and inflation uncertainty, the sign difference has to be driven by a negative correlation of expectation stock market and inflation uncertainty. In order to reach more conclusive statements, I will examine how perceived labor income risks correlate with the realized stock market returns and indicators of business cycles depending upon individual factors in the next step of the analysis.

To summarize, a few questions arise from the patterns discussed above. First, what drives the differences in subjective earning risks across different workers? To what extent these perceptive differences reflect the true heterogeneity of the income risks facing by these individuals? Or they can be attributed to perceptive heterogeneity independent from the true risk profile. Second, how are individual earning risk is correlated with asset return expectations and broadly the macroeconomic environment? This will be the focus of the coming sections.

3.5 Perceived income risks and decisions (in progress)

This section investigates how individual-specific perceived risks are correlated with household economic decisions such as consumption and labor supply. I should note that the purpose of this exercise is not primarily for causal inference at the current stage. Instead, it is meant to check if the surveyed households demonstrate a certain degree of in-survey consistency in terms of their perceptions and decision inclinations.

In particular, I ask two questions based on the available survey answers provided by the core module of the survey. First, are higher perceived income risks associated with a lower anticipated household spending growth? Second, are higher perceived income risks are associated with actions of self-insurance such as seeking an alternative job. This can be indirectly tested using the surveyed probability of voluntary separation from the current job. In addition, supplementary modules of SCE have also surveyed more detailed questions on spending decisions and the labor market. (These I will examine in the next stage of the analysis.)

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.

The empirical results will be reported in the next version of the draft.

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 $\hat{\sigma}^2$.

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

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.

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

where $\tilde{\Omega}_{t-k}$ is the perceived variance-covariance of income and income shocks within each point of time.

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

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, $\tilde{\Omega}_t$ 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.)

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

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

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

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 5.)
- 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 6. 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.

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

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. 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 7. 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 8 and 9 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 13 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

This paper first documents following empirical findings of perceived income risks.

- Individuals' perceived income risks measured by variance, IQR and tail risk measure skewness all exhibit sizable dispersion across different individuals. This pattern also holds for real earning risk, when adjusted by inflation uncertainty.
- Distributions of perceived risks are consistent with a number of intuitive patterns. For instance, earners who are males, from higher-income households, and with higher education have statistically significantly lower perceived risks.
- The perceived risk is also positively associated with the perceived chance of unemployment.

Preliminary findings include the following.

- Perceived risk and skewness for future income are negatively correlated with stock market returns in the same future horizon. (This needs to be more disciplined by the empirical asset pricing literature.)

To-dos in the next stage of the work

- Empirically, investigate the correlation between perceived risk and high-frequency macro variables that can approximate business cycle dynamics.
- To decompose the subjective income process by addressing the time aggregation problem and missing data on monthly earnings.
- Theoretically, build a life cycle model of consumption/portfolio choice with the following features: - heterogeneous perceptions of income process, which is micro-founded in a manner in line with the empirical patterns. - with endogenous consumption and portfolio choice decisions. - with market incompleteness, i.e. the idiosyncratic risks are uninsured.

6 Appendix

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Table 1: Current Labor Market Conditions and Perceived Income Risks

	median:var	median:iqr	median:rvar	median:skew	mean:var	mean:iqr	mean:rvar	mean:skew
0	-0.15	-0.15	-0.53***	nan	-0.24**	-0.36***	-0.47***	0.06
1	-0.01	0.01	-0.55***	nan	-0.44***	-0.53***	-0.56***	0.18
2	-0.09	-0.07	-0.45***	nan	-0.37***	-0.42***	-0.43***	0.01
3	-0.09	-0.09	-0.46***	nan	-0.4***	-0.43***	-0.41***	-0.13
4	-0.27**	-0.24*	-0.49***	nan	-0.28**	-0.38***	-0.31**	-0.18

*** $p<0.001$, ** $p<0.01$ 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 $t, t-1, ..., t-k$.

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Table 2: Perceived Income Growth and Individual Characteristics

	incexp I	incexp II	incexp III	incexp IIII	rincexp I	rincexp II	rincexp III	rincexp IIII
HHinc_gr=low inc			-0.03				-0.37***	
			(0.02)				(0.03)	
educ_gr=low educ				-0.25***				-0.62***
				(0.02)				(0.03)
gender=male				-0.33***				-0.78***
				(0.02)				(0.03)
parttime=yes	-0.42***	-0.34***	-0.33***		-0.56***	-0.47***	-0.38***	
	(0.03)	(0.03)	(0.03)		(0.04)	(0.04)	(0.04)	
selfemp=yes	0.86***	-0.00***	-0.00***		0.83***	-0.00***	0.00***	
	(0.04)	(0.00)	(0.00)		(0.05)	(0.00)	(0.00)	
Intercept	2.82***	2.64***	2.65***	3.06***	-0.28***	-0.51***	-0.40***	0.23***
	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)
	0.01	0.02	0.02	0.01	0.01	0.04	0.05	0.02
Stkprob		0.01***	0.01***			0.02***	0.02***	
		(0.00)	(0.00)			(0.00)	(0.00)	
UEprobAgg		-0.00***	-0.00***			-0.01***	-0.01***	
		(0.00)	(0.00)			(0.00)	(0.00)	
UEprobInd		-0.01***	-0.01***			-0.01***	-0.01***	
		(0.00)	(0.00)			(0.00)	(0.00)	
N	52102	47112	47112	45745	47728	43099	43099	41908
R2	0.01	0.02	0.02	0.01	0.01	0.04	0.05	0.02

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

This table reports regression results of perceived labor income(incexp for nominal, rincexp for real) growth on household specific variables. HHinc: household income group ranges from lowests (=1, less than $10k/year) to the heightst (=11, greater than $200k/year). Education, educ ranges from the lowest (=1, less than high school) to the highest (=9).

Table 3: Perceived Income Risks and Individual Characteristics

	incvar I	incvar II	incvar III	incvar IIII	rincvar I	rincvar II	rincvar III	rincvar IIII
HHinc_gr=low inc			1.52***				6.97***	
			(0.10)				(0.20)	
educ_gr=low educ				0.44***				4.01***
				(0.12)				(0.22)
gender=male				-0.82***				2.67***
				(0.10)				(0.19)
parttime=yes	0.25*	0.35***	-0.02		1.90***	2.23***	0.56**	
	(0.13)	(0.13)	(0.14)		(0.25)	(0.27)	(0.27)	
selfemp=yes	7.58***	-0.00	-0.00**		6.72***	-0.00***	-0.00***	
	(0.15)	(0.00)	(0.00)		(0.29)	(0.00)	(0.00)	
Intercept	4.62***	3.76***	3.30***	5.71***	12.42***	12.26***	10.22***	11.21***
	(0.05)	(0.12)	(0.13)	(0.08)	(0.10)	(0.25)	(0.25)	(0.14)
	0.05	0.00	0.01	0.00	0.01	0.01	0.04	0.01
Stkprob		0.01***	0.01***			-0.06***	-0.05***	
		(0.00)	(0.00)			(0.00)	(0.00)	
UEprobAgg		0.00**	0.00			0.05***	0.04***	
		(0.00)	(0.00)			(0.00)	(0.00)	
UEprobInd		0.03***	0.03***			0.05***	0.04***	
		(0.00)	(0.00)			(0.00)	(0.00)	
N	51788	45903	45903	45430	48665	43077	43077	42654
R2	0.05	0.00	0.01	0.00	0.01	0.01	0.04	0.01

Standard errors are clustered by household. *** p<0.001, ** p<0.01 and * p<0.05.
This table reports regression results of perceived income risks (incvar for nominal, rincvar for real) on household specific variables. HHinc: household income group ranges from lowests (=1, less than $10k/year) to the heightst (=11, greater than $200k/year). Education, educ ranges from the lowest (=1, less than high school) to the highest (=9).

Table 4: Correlation between Perceived Income Risks and Stock Market Return

	median:var	median:iqr	median:rvar	median:skew	mean:var	mean:iqr	mean:rvar	mean:skew
0	-0.11	-0.11	-0.07	nan	-0.04	-0.03	-0.05	0.01
1	-0.12	-0.1	0.05	nan	0.04	0.06	0.09	-0.14
2	-0.21*	-0.23*	0.06	nan	0.01	-0.01	0.21*	-0.11
3	-0.14	-0.11	-0.01	nan	-0.06	-0.08	0.15	-0.23*
4	-0.04	0.03	-0.12	nan	-0.21*	-0.22*	-0.12	0.01
5	-0.05	-0.01	-0.19	nan	-0.18	-0.18	-0.24*	0.01
6	-0.09	-0.09	-0.24*	nan	-0.16	-0.19	-0.22*	-0.12
7	-0.19	-0.24*	-0.33***	nan	-0.09	-0.16	-0.12	-0.2
8	-0.08	-0.1	-0.19	nan	-0.15	-0.21	-0.11	-0.15
9	0.02	0.03	-0.02	nan	-0.23*	-0.25*	-0.16	0.02
10	0.1	0.11	0.0	nan	-0.26**	-0.24*	-0.08	-0.07
11	0.02	0.04	0.03	nan	-0.04	-0.07	0.04	-0.1
12	0.12	0.11	-0.03	nan	-0.02	-0.02	-0.04	-0.1

*** $p<0.001$, ** $p<0.01$ 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 monthly s&p500 return by the end of $t+k$ for $k=0,1,..,11$.

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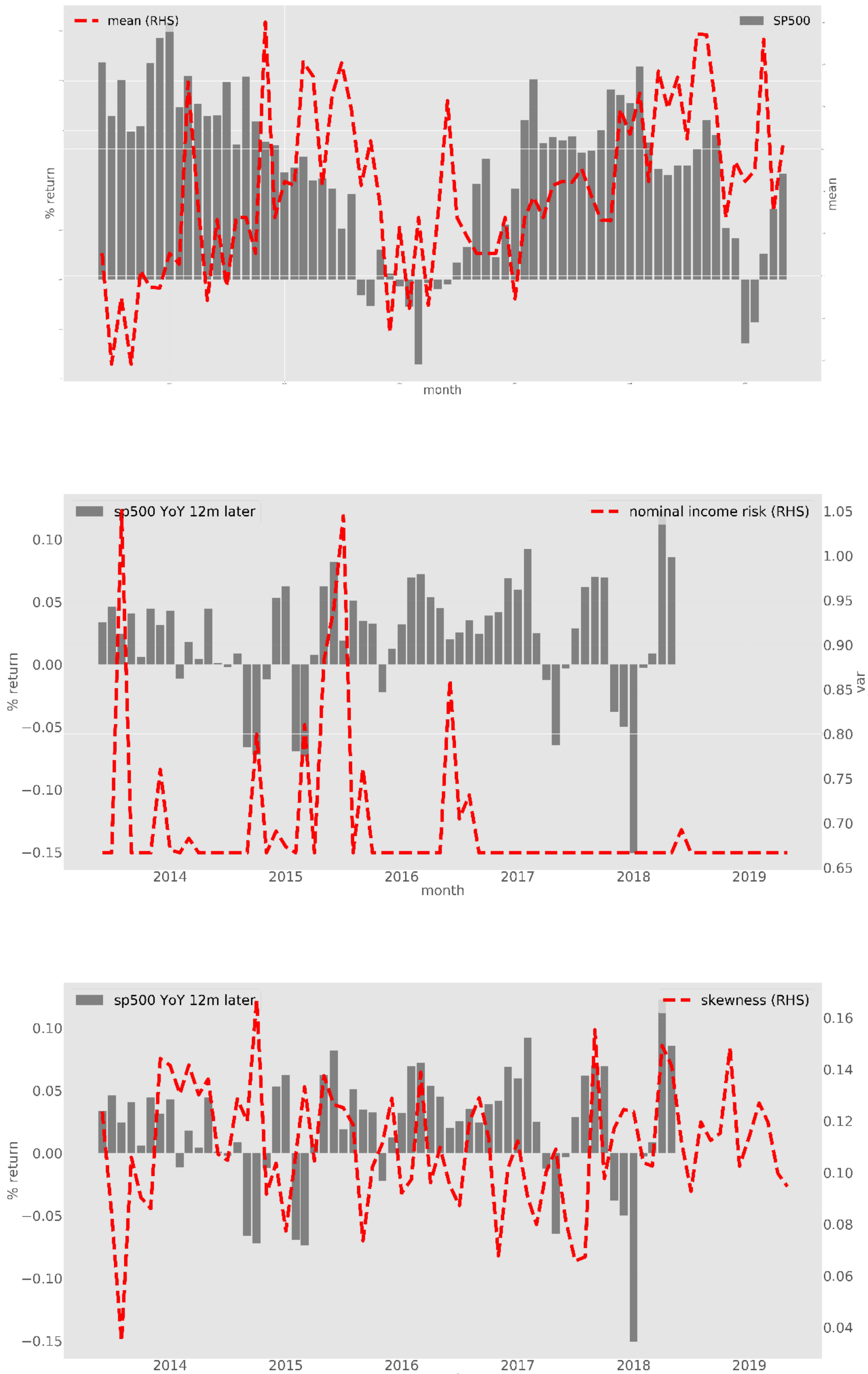

Figure 3: Perceived Income Risks and Stock Market Return

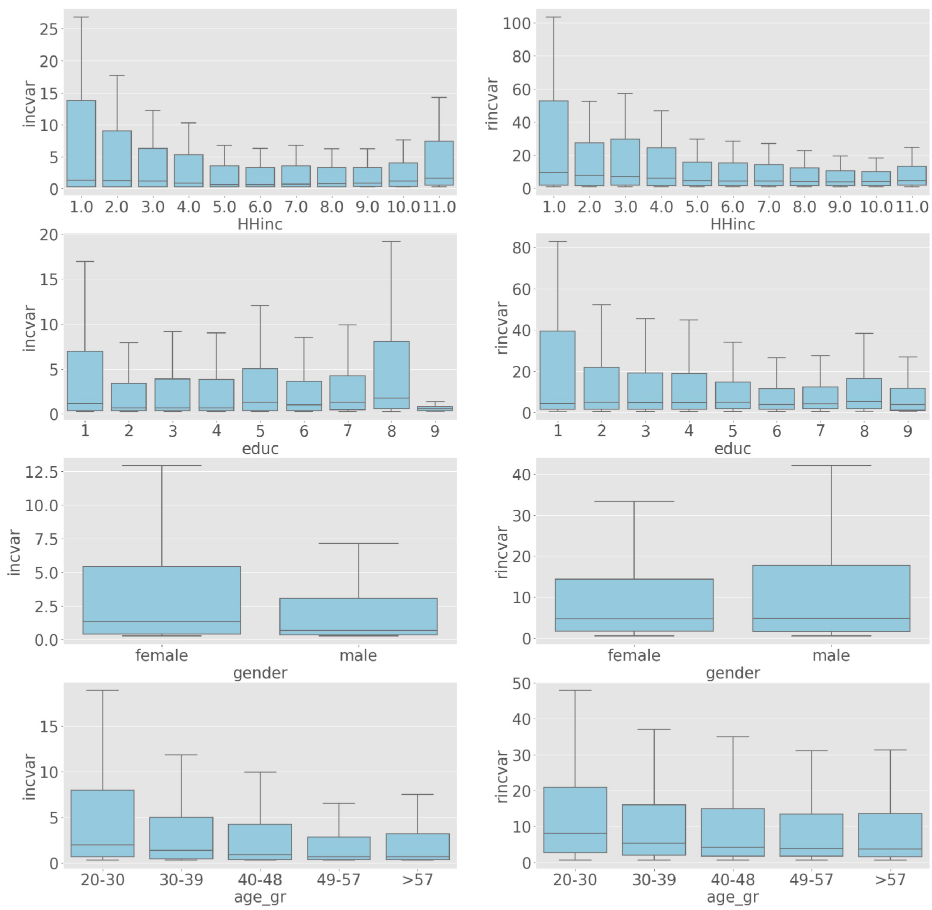

Figure 4: Perceived Income by Group

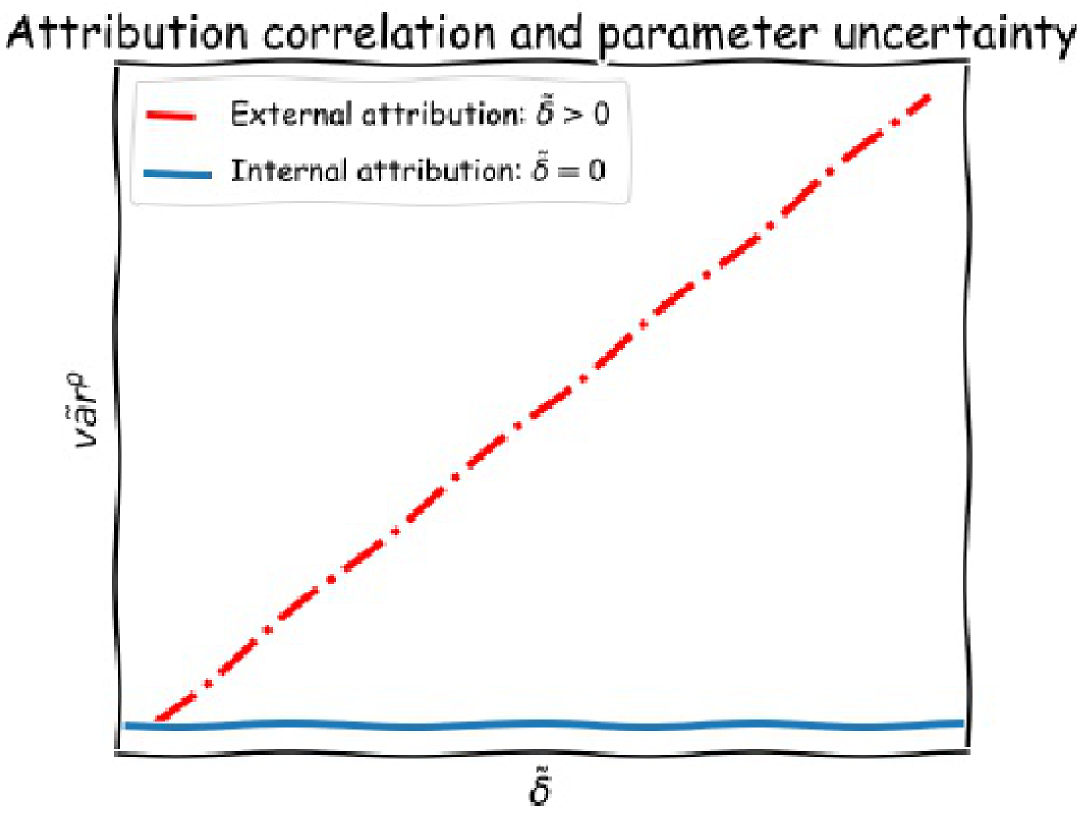

Figure 5: Attribution and Parameter Uncertainty

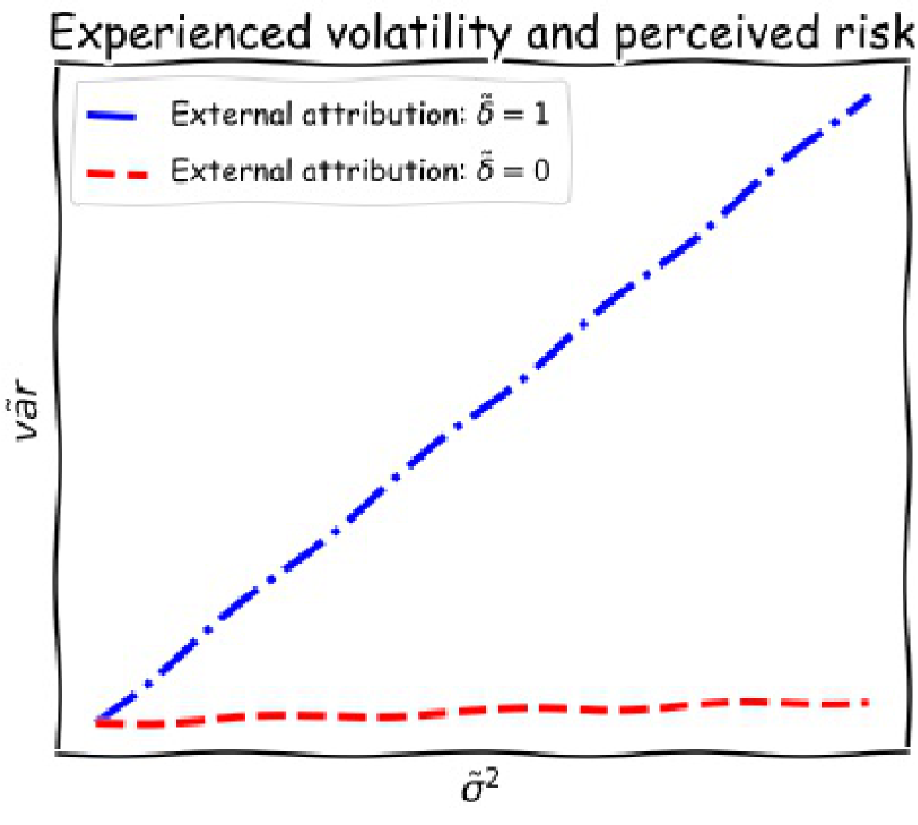

Figure 6: Experienced Volatility and Perceived Risk

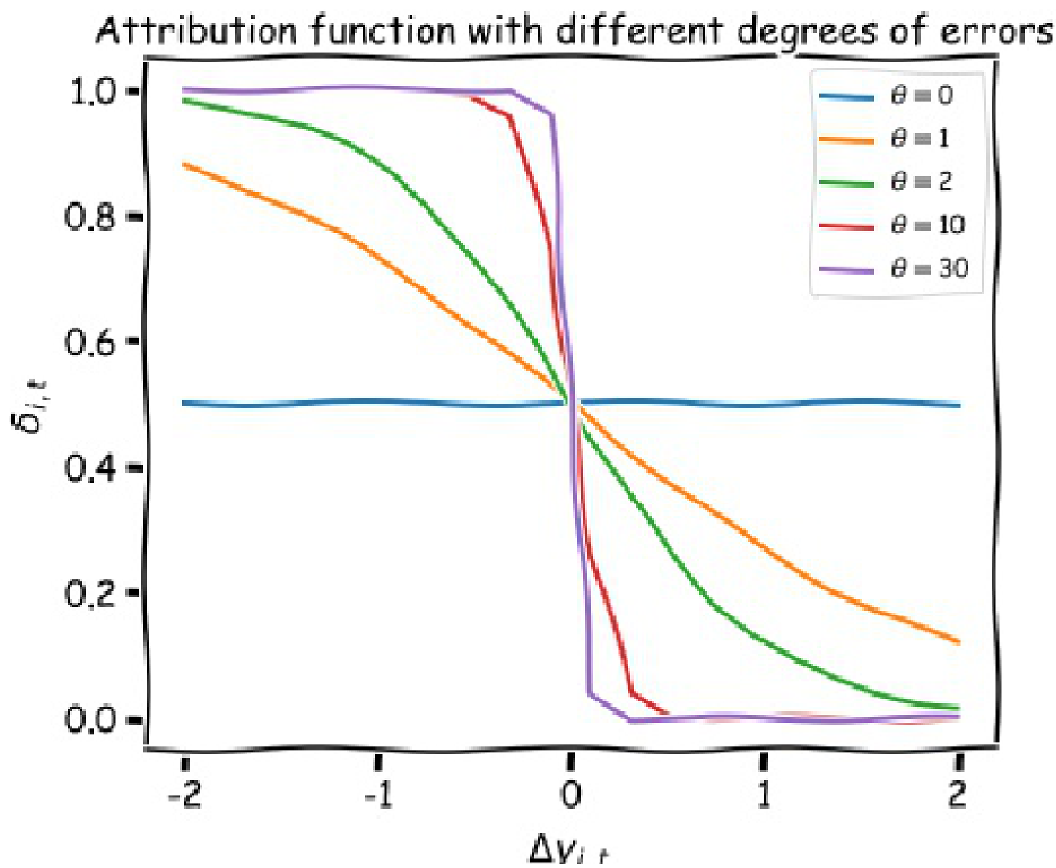

Figure 7: Attribution Function

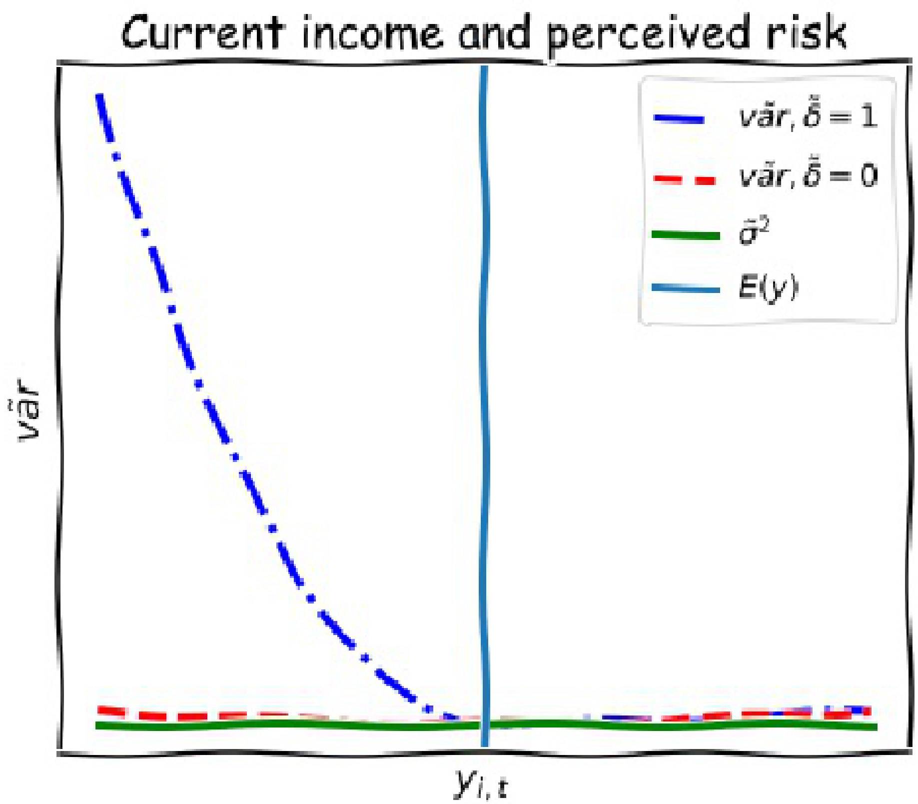

Figure 8: Current Income and Perceived Risk

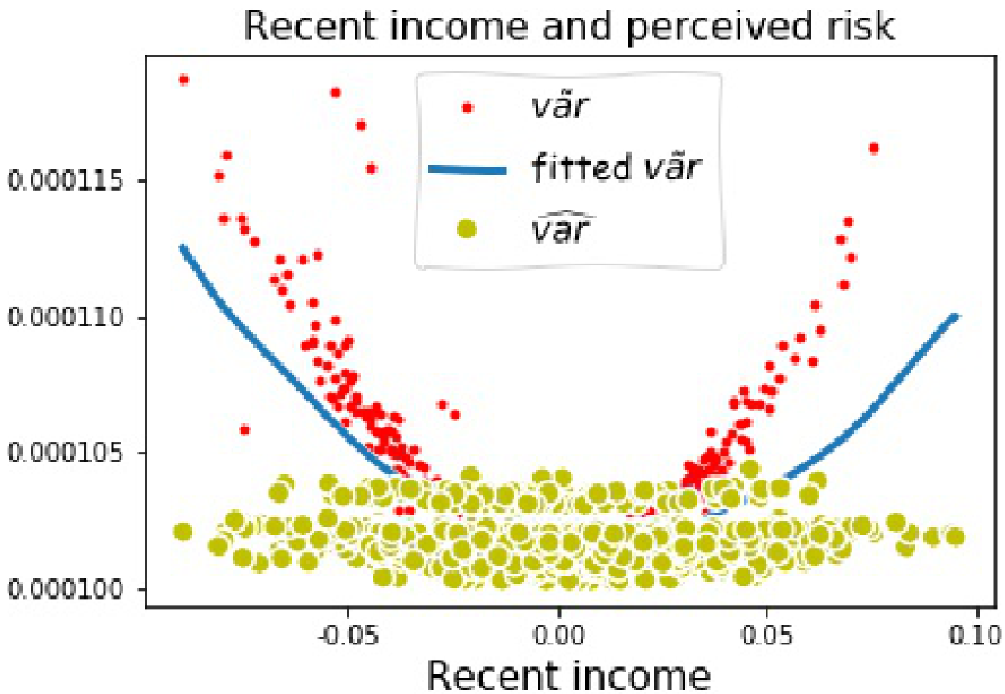

Figure 9: Simulated Income Profile of Perceived Risk

Table 5: Perceived Income Risks and Household Spending

	spending I	spending II	spending III	spending IIII	spending IIIII	spending IIIIII	spending IIIIIII
Intercept	3.46***	4.23***	4.29***	3.73***	4.67***	3.21***	4.63***
	(0.31)	(0.07)	(0.22)	(0.26)	(0.31)	(0.72)	(0.20)
	0.00	0.00	0.00	0.00	0.00	0.00	0.00
UEprobAgg						0.04***	
						(0.02)	
UEprobInd					-0.01		
					(0.01)		
incexp	0.39***						
	(0.08)						
incskew							0.19
							(0.45)
incvar			0.07***				
			(0.02)				
rincexp		-0.04*					
		(0.02)					
rincvar				0.07***			
				(0.01)			
N	53455	48983	53171	49986	52632	76531	52751
R2	0.00	0.00	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).

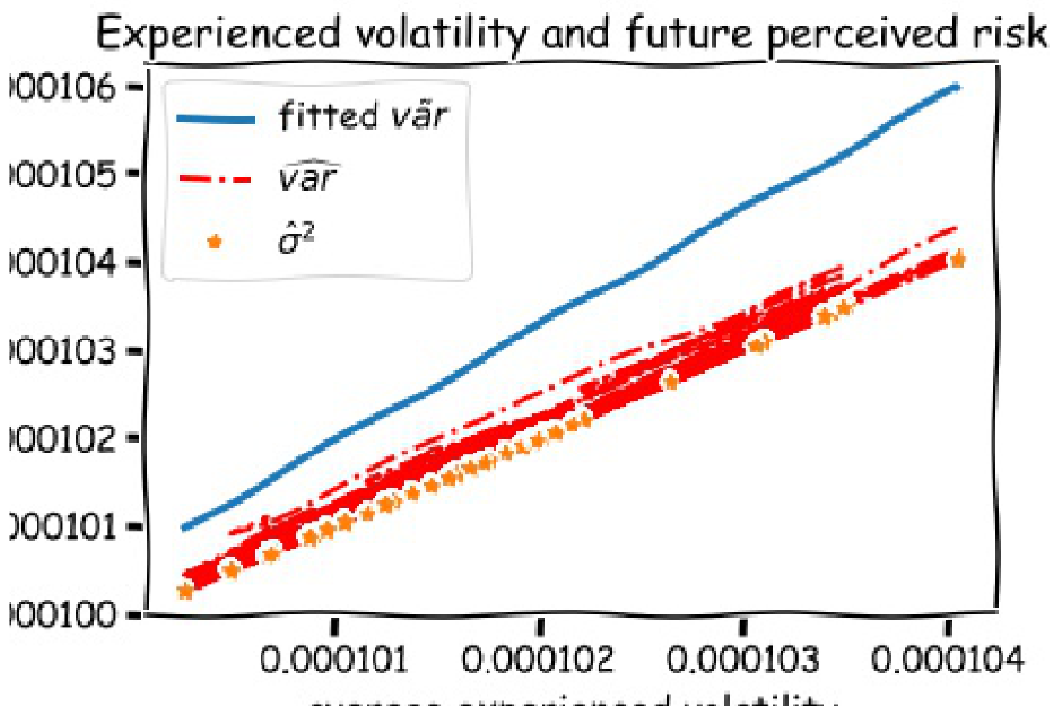

Figure 10: Simulated Experience of Volatility and Perceived Risk

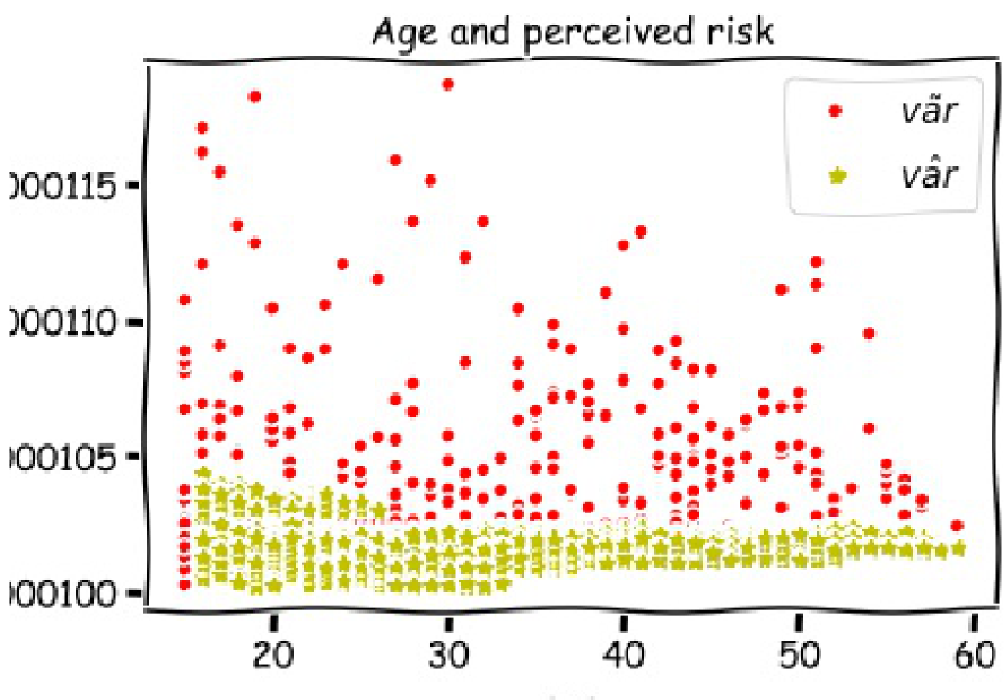

Figure 11: Simulated Age Profile of Perceived Risk

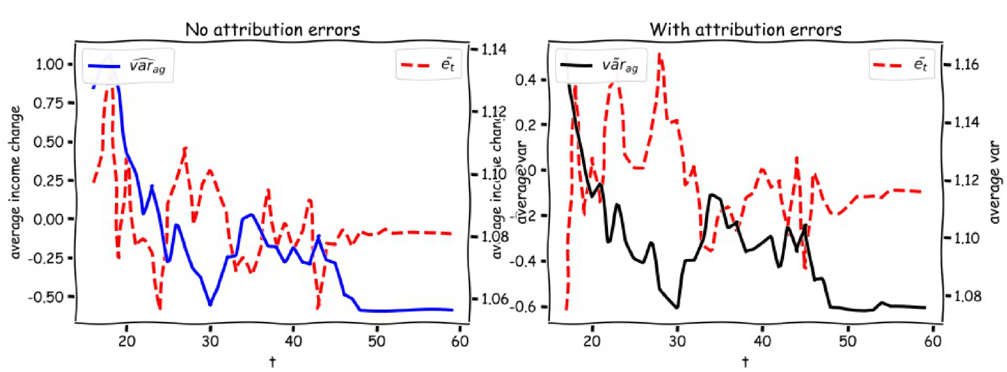

Figure 12: Simulatd Average Labor Market and Perceived Risk

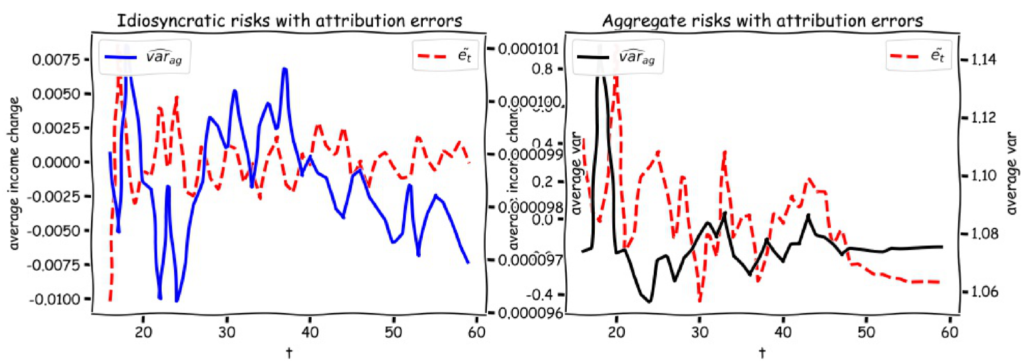

Figure 13: Simulated Average Labor Market Outcome and Perceived Risk