Cyclical Labor Income Risk*

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July 8, 2019

Abstract

We investigate cyclicality of variance and skewness of household labor income risk using PSID data. There are five main findings. First, we find that head's labor income exhibits countercyclical variance and procyclical skewness. Second, the cyclicality of hourly wages is muted, suggesting that head's labor income risk is mainly coming from the volatility of hours. Third, younger households face stronger cyclicality of income volatility than older ones, although the level of volatility is lower for the younger ones. Fourth, while a second earner helps lower the level of skewness, it does not mitigate the volatility of household labor income risk. Meanwhile, government taxes and transfers are found to mitigate the level and cyclicality of labor income risk volatility. Finally, among heads with strong labor market attachment, the cyclicality of labor income volatility becomes weaker, while the cyclicality of skewness remains.

Keywords: Labor income risk, income inequality, business cycles
JEL: D31, E24, E32, H31, J31

*We thank the Opportunity and Inclusive Growth Institute of the Federal Reserve Bank of Minneapolis, where this project was initiated. We thank seminar participants at the MMM 2018 (Nashville) and LACEA 2018 (Guayaquil). The views expressed here do not necessarily reflect those of the Federal Reserve Bank of Philadelphia, the Federal Reserve Bank of Minneapolis, or the Federal Reserve System.

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1 Introduction

How does individual labor income risk change between economic expansions and contractions? What drives the cyclical nature of labor income risk — wages or hours? How effective are private (through the second earner) and public (through government taxes and transfers) insurance channels in stabilizing labor income risk? We address these questions by estimating time-varying second and third moments of earnings shocks for several income types, using the Panel Study of Income Dynamics (PSID).

At the conceptual level, what we do in this paper is to systematically analyze cyclicality of risk for several income definitions within an unified estimation framework. We extend the econometric technique proposed by Storesletten, Telmer and Yaron (2004), which is designed to estimate the parameters of income shocks with a time-varying second moment (variance), by augmenting it to handle a time-varying third moment (skewness). The list of income definitions we consider includes individual (head's) hourly wages and labor income, joint (head and wife's) labor income, and post-government (taxes and transfers) joint labor income. We also consider head's labor income for a subsample of heads with strong labor market attachment (Abowd and Card, 1989; Meghir and Pistaferri, 2004; Guvenen, Ozkan and Song, 2014), identified by labor income exceeding a certain income threshold. For the sake of convenience, hereafter we refer to the head's labor income defined this way as a *narrowly defined* head's labor income.

There are five main results. First, head's labor income exhibits countercyclical income risk, in the sense that both variance (countercyclical variance) and right skewness (procyclical skewness) increase in contractions. Second, head's hourly wage is less cyclical than head's labor income in both variance and skewness. This implies that changes in hours, possibly due to unemployment, are behind the cyclicality of head's labor income risk. Third, we look at younger and older households separately. While older households face a higher level of labor income variance than younger ones, younger households exhibit stronger cyclicality of labor income volatility; the difference of variance of labor income risk between expansions and recessions is significantly larger for younger households.

Fourth, we investigate the role of private (through labor income of the second earner) and public (through government taxes and transfers) insurance in mitigating the level and cyclicality of labor income risk. We find that existence of the second earner lowers the overall *level* of skewness of income risk but not *cyclicality*. Effects on variance of labor income risk are limited. On the other hand, government taxes and transfers are found to lower both the *level* and the *cyclicality* of labor income risk that households are facing. When we compute the implied probability of disaster (defined as a decline in residual labor income of more than 50% or 100%), both the private and public insurance channel are found to mitigate the increase in disaster probabilities in contractions. With the second earner, then increase in the probability of a disaster in contractions is mitigated by 40-60%. Government taxes and transfers mitigate such increase in the probability of a disaster in recessions by 30-50%.

Finally, we investigate what contributed to the seemingly opposite findings between Storesletten, Telmer and Yaron (2004), who find countercyclical variance of labor income risk, and Guvenen, Ozkan and Song (2014) and Busch, Domeij, Guvenen and Madera (2018), who find acyclical variance and procyclical skewness of labor income risk. We find that using narrowly-defined head's labor income and not including government transfers by the latter

partially explain the differences between the two. When we look at cyclicality of narrowly-defined head's labor income, cyclicality of variance is found to be sizably weaker than that of head's labor income. Additionally, government taxes and transfers also ameliorate cyclicality of variance. On the other hand, narrowly-defined head's labor income exhibits cyclicality of skewness as strongly as head's labor income.

We contribute to the literature of understanding individual labor income risk by studying both variance and cyclicality of labor income risk for various definitions of labor income. Storesletten, Telmer and Yaron (2004) serves as the classic benchmark in the literature. They propose a novel estimation methodology of the countercyclical income risk and find that standard deviation of labor income shocks is 80% higher in recessions than in expansions. We extend their study in three ways. First, we allow time-varying skewness in addition to time-varying volatility. Second, we investigate 5 definitions of labor income, which allows us to study roles of various factors affecting cyclicality of labor income risk, such as second earners and government taxes and transfers. Third, we look at cyclicality of labor income risk for older and younger households separately.

In a more recent contribution, Guvenen, Ozkan and Song (2014) reach a seemingly opposite conclusion. The authors draw from a large administrative panel dataset and find that the second moment is remarkably stable across economic expansions and contractions, while the third moment exhibits a strong cyclicality. They find that, in recessions, the left tail of the income growth distribution expands, while the right tail gets compressed. They conclude that what previous research was interpreting as a countercyclical variance turns out to be a procyclical skewness. In a follow-up work, Busch, Domeij, Guvenen and Madera (2018) also find acyclical variance and procyclical skewness in German, Sweden, and the U.S., with the PSID data. We contribute to accounting for the differences by employing the empirical methodology of Storesletten, Telmer and Yaron (2004) but investigating cyclicality of skewness, and employing the sample selection criteria of Guvenen, Ozkan and Song (2014) in one of our definitions of labor income.

Deepening our understanding of labor income risk is important as labor income risk, together with market incompleteness, is found to be crucial in many important questions in macroeconomics. The literature of studying the role of labor income risk in macroeconomics goes back to Deaton (1992). Storesletten, Telmer and Yaron (2001) argue that the cost of business cycles changes significantly if the cyclical movement of labor income risk is taken into account. Kaplan and Violante (2010) find the degree of consumption smoothing depends on the nature of labor income risk — whether it is persistent or transitory. Heathcote, Storesletten and Violante (2010b) explore the welfare implications of the increasing wage volatility in the U.S. and find that it benefits recent generations of workers as the higher educational premium improves college attainment and redistributes labor within the household. Guvenen, Karahan, Ozkan and Song (2019) document a related empirical regularity: they show that in the data, the income growth rate is very small for most individuals, while there is a considerable mass of people with very large growth rates. Therefore, high-order moments (kurtosis in this case) are important features of income growth distribution. In macro-finance literature, Constantinides and Duffie (1996) and Storesletten, Telmer and Yaron (2007) find that considering labor income risk could partially solve the risk premium puzzle.

The rest of paper is organized as follows. Sections 2 and 3 describe the data and lay

out the estimation methodology. In Section 4, we estimate and analyze individual labor income risk with time-varying variance for various definitions of labor income. We extend the methodology to allow for time-varying skewness as well in Section 5. We provide economic interpretation in Section 6. Section 7 concludes.

2 Data

We draw on the Panel Study of Income Dynamics (PSID) data, which is the longest publicly-available panel data on the U.S. population. PSID started in 1968, with more than 2,000 U.S. families being interviewed on a broad set of topics. The "split-off" families (when family members move out and establish their own households) are also interviewed. PSID spans the time period 1968-2014.

The advantage of this dataset for our purposes is the possibility to simultaneously observe several types of labor income. In particular, we consider 5 different definitions of labor income:

1. head's hourly wage[1],
2. head's labor income,
3. head's labor income (narrow definition),
4. joint labor income (head + wife combined),
5. post-government (taxes and transfers) joint labor income.

As it was mentioned in Section 1, *narrowly defined* head's labor income refers to those observations for which the labor income exceeds some minimum threshold. This is intended to capture individuals with a strong labor-market attachment. In particular, the income threshold is defined as half of an hourly minimum wage multiplied by 520 hours (13 weeks at 40 hours per week). The post-government joint labor income is equal to the joint labor income (head and wife's labor income combined) plus government transfers (unemployment compensation, disability insurance and alike) minus taxes (federal and state). PSID provides imputed values of taxes for some years (1978-1990), but we opt to use as many years of data as possible and, therefore, use TAXSIM to obtain our own estimates of state and federal government tax liabilities for the sample of households. The TAXSIM, however, is capable of computing the taxes starting from 1978 — no state-level tax regulations are available prior to that year — which forces us to restrict the sample to the years 1978-2014. Detailed explanations of how the variables have been constructed are delegated to Appendix A.1.

PSID is a survey data which suffers from well-known issues, such as top-coding of labor income, potential misreporting of income and a small sample size. We, however, argue that

[1] Throughout the paper, we stick to PSID terminology and call a male earner (the husband) a household's head, unless it is a family with a female being the only earner (in this case, the wife is the head). A natural alternative is to mark the top earner within the family as its "head"; this, however, will make our exercise not directly comparable to previous studies based on PSID data, and we, therefore, opt to use a conventional definition instead.

PSID is an appropriate source of data for our exercise for several reasons. First, we are interested in several types of labor income, which necessitates the knowledge of labor income separately for each spouse, transfers received, wages and hours. This information is typically not simultaneously available in other datasets.

Second, while the top-coding problem is particularly acute for studying income inequality (especially at the right tail of distribution), in this paper, we are primarily interested in general swings of income risk over the business cycle. We, therefore, do not expect this issue to affect our results considerably.

Finally, there is a technical issue with changing frequency: the years 1969-1995 are covered with annual frequency, while the years 1996-2014 are covered with biannual frequency. As it will become clear in Section 3, it is straightforward to handle the gaps in data using our methodology.

The rest of this section — Sections 2.1 and 2.2 — discusses sample selection and identification of business cycles.

2.1 Sample Selection

We closely follow the sample selection strategy of Storesletten, Telmer and Yaron (2004). In PSID, the object of analysis is a family unit (FU). We track heads of FUs as follows: if the FU contains a married couple, then the husband is arbitrarily assigned to be the head. A woman can be the head only if the husband is missing. In our analysis, we treat split-off families as new independent families: that is, when the head of the household changes, we record it as a new family unit.

Next, we apply a series of selection criteria to construct our dataset. First, an FU is in our sample as long as e head is between 23 and 60 years old. By doing so, we pick only those households where the head has a sufficiently strong labor market attachment.

Second, we drop all families with zero or negative total labor income in any year. We also drop families with an anomaly in labor income growth rates[2] (Meghir and Pistaferri, 2004; Storesletten, Telmer and Yaron, 2004). Observations with top-coded values are also dropped.

Finally, we drop families that are part of the Survey of Economic Opportunity (1968 ID $\in [5000, 7000]$) or the Latino subsample (1968 ID > 7000). This leaves us with approximately 55,000 observations. Table 1 provides the summary statistics for the final dataset.

Appendix A.2 provides more details on the process of sample selection. Table A.1 reports the number of observations retained at each step of data preparation.

2.2 Identifying Business Cycles

The is no unique way to classify years into "expansions" and "contractions". Even though PSID is the longest available panel dataset, its time span covers few recessionary periods

[2]That is, we keep household i as long as

$$\ln\left(\frac{y_{it}}{y_{it-1}}\right) \in \left(\frac{1}{20}, 20\right) \ \forall t.$$

Table 1: Summary Statistics

	Wage	Head's LI	Head's LI (narrow)	Joint LI	Post-Govt LI
Min	0	0.21	248.05	0.23	372.06
Max	11.80	45,471.57	45,471.57	46,977.23	33,921.60
Median	3.13	6,912.93	6,953.65	9,148.92	8,056,87
Std	2.00	4,390.63	4,362.79	6,049.04	4,572.23
Bottom 5%	0.64	1,643.49	1,803.11	2,187.22	2,620.69
Top 5%	7.19	15,709.26	21,421.60	28,726.57	17,198.53

Notes: Table 1 reports the summary statistics for the final dataset based on PSID raw data from the years 1978-2014 (see Appendix A.2 for details on data construction). The description of income variables (wages, head's LI, head's LI (narrow), joint LI, post-government joint LI) is discussed in full detail in Appendix A.1. All variables are converted into real terms using CPI with 1968 being the base year.

as defined by NBER[3]. It has become a working standard in the literature to classify years into stages of the business cycle based on whether the growth rate of some macro aggregate was above or below the long-run mean in that particular year: Storesletten, Telmer and Yaron (2004) use GNP per capita, Lee and Mukoyama (2015) and Moreira (2016) use real GDP. We opt to use the real GNP per capita growth rate as a determinant of economic expansions and contractions in our estimation exercise, leaving the discussion of alternatives to Appendix B. One of the reasons we prefer the GNP per capita growth rate is that it keeps our exercise close to Storesletten, Telmer and Yaron (2004), which is important for comparison purposes. Appendix A.5 shows that classifications based on GDP and GNP per capita yield comparable results.

3 Estimation Methodology

We follow the estimation methodology proposed by Storesletten, Telmer and Yaron (2004) for three reasons. First, this is a parsimonious way to estimate time-varying variance, and estimates reported by Storesletten, Telmer and Yaron (2004) serve as a natural reference point. Second, the parametric assumptions this methodology relies on help mitigate small-sample size issues, which are typical for easy-to-access datasets. Third, this methodology can be extended to allow for a time-varying skewness (see Section 5.3). Finally, the methodology can easily accommodate the change in the frequency of PSID from annual to biennial in the middle of the sample period (1996). We next give a brief summary of the estimation methodology in Section 3.1 and then provide an identification argument on the workings of this method in Section 3.2.

3.1 Overview

Let y_{it}^h be log labor income of household i of age h in year t. We first project log labor income on a set of observables:

$$y_{it}^h = g(x_{it}^h, Y_t) + u_{it}^h, \tag{1}$$

[3]Recessionary years according to NBER are 1970, 1974-75, 1981-82, 1991, 2001, 2008-09.

where x_{it}^h is the deterministic component of household-specific income attributable to age, education, and family size. Y_t is a measure of aggregate conditions at time t, which picks up the business cycle component of individual labor income.

The residual u_{it}^h is a random component that under standard assumptions satisfies the orthogonality condition

$$\mathbb{E}(u_{it}^h | Y_t, x_{it}^h) = 0 \quad \forall t.$$

Intuitively, the residual captures variation in labor income that cannot be attributed to personal characteristics (such as differences in education) and is not explained by the aggregate conditions (information contained in Y_t).

Next, several parametric assumptions are imposed. In particular, it is assumed that the idiosyncratic earnings component u_{it}^h follows the process:

$$\begin{aligned} u_{it} &= \alpha_i + z_{it} + \varepsilon_{it} \\ z_{it} &= \rho z_{i,t-1} + \eta_{it}. \end{aligned} \tag{2}$$

Here α_i is a time-invariant fixed effect that household i draws at the beginning of its labor market life. Next, ε_{it} is a purely transitory component, while z_{it} is a persistent earnings component that follows an AR(1) process. For now, innovations to both persistent and transitory components, as well as individual fixed effects are normally distributed, but later we assume that innovations to the persistent component to be drawn from a *skew normal distribution*, to accommodate time-varying skewness of labor income risk (Section 5.3):

$$\begin{aligned} \alpha_i &\sim \mathcal{N}(0, \sigma_\alpha^2), \\ \varepsilon_{it} &\sim \mathcal{N}(0, \sigma_\varepsilon^2), \\ \eta_{it} &\sim \mathcal{N}(0, \sigma_t^2). \end{aligned}$$

The model is capable of picking up the countercyclicality of labor income risk, since it allows the variance of innovations to the persistent component η_{it} to be a function of the aggregate state:

$$\sigma_t^2 = \begin{cases} \sigma_E^2 \text{ if expansion at } t \\ \sigma_C^2 \text{ if contraction at } t. \end{cases} \tag{3}$$

Therefore, there are 5 parameters to estimate:

$$\Theta = \{\rho, \sigma_\alpha^2, \sigma_\varepsilon^2, \sigma_E^2, \sigma_C^2\}.$$

We estimate Θ by GMM, using the moment conditions that relate the cross-sectional variance of estimated residuals, $\hat{u}_{it}^h$, with the history of shocks households experienced throughout their labor market life.[4] Using normality and independence assumptions, we can express the

[4] We assume that individuals enter labor market at the age of 23.

variance of a labor income shock of family i with the head aged h in year t as:

$$\begin{aligned}\mathrm{Var}(u_{it}^h) &= \mathrm{Var}(\alpha_i + z_{it} + \varepsilon_{it}) \\ &= \sigma_\alpha^2 + \sigma_\varepsilon^2 + \mathrm{Var}(\rho z_{it-1} + \eta_{it}) \\ &= \sigma_\alpha^2 + \sigma_\varepsilon^2 + \sum_{j=0}^{h-1} \rho^{2j} \left[I_{t-j}\sigma_E^2 + (1 - I_{t-j})\sigma_C^2 \right]. \end{aligned} \tag{4}$$

In Equation (4), I_t is an indicator of an aggregate expansion in year t. The sample analog of the population moment (4) takes the form:

$$\frac{1}{N_{ht}} \sum_{i=1}^{N_{ht}} \left\{ (u_{it}^h)^2 - (\sigma_\alpha^2 + \sigma_\varepsilon^2) - \sum_{j=0}^{h-1} \rho^{2j} [I_{t-j}\sigma_E^2 + (1 - I_{t-j})\sigma_C^2] \right\} = 0. \tag{5}$$

Here, N_{ht} is the number of families at time t with a head aged h. Note that σ_α and σ_ε are not identified separately: Storesletten, Telmer and Yaron (2004) use extra moment conditions (with autocovariances of u_{it}^h) in order to disentangle these two parameters.[5] In this paper, we are not interested in either of those parameters separately, and, hence, estimate the sum of σ_α^2 and σ_ε^2.[6]

There are in total $H \times T$ moments of type (5), with H denoting the number of different ages in the data, and T the number of available years.[7] Furthermore, we "aggregate" the moment conditions so that the number of observations in any $\{H, T\}$ - cell does not fall below 100. To accomplish this, we break down all feasible ages 23-60 into 4 age groups indexed by $h \in \{25, 35, 45, 55\}$ and make each group contain ages ± 5 years, with group $h = 25$ being an exception.[8] These adjustments help us balance the two opposing forces: on the one hand, the more moments conditions we use, the more information we extract from the data; on the other hand, more moment conditions lead to some (age, year)-cells being too small.[9]

3.2 Identification

The way estimation is set up in Section 3.1 highlights its benefits (see Equation (4)): even though there are very few families in the dataset whose working life we observe entirely — from the year its head enters the labor market till the year he/she retires — we can still incorporate the entire history of business cycle fluctuations that every household experienced over its lifetime into the estimation. In other words, the use of cross-sectional moments for identification allows us to exploit macroeconomic information that predates the micro panel, thereby incorporating more business cycles in the analysis than covered by the sample.

[5] Specifically, Storesletten, Telmer and Yaron (2004) obtain $\sigma_\alpha^2 + \sigma_\epsilon^2 = 0.316$ when they do not disentangle the two and $\sigma_\alpha^2 = 0.201$ and $\sigma_\epsilon^2 = 0.123$ when the two variances are separately identified.

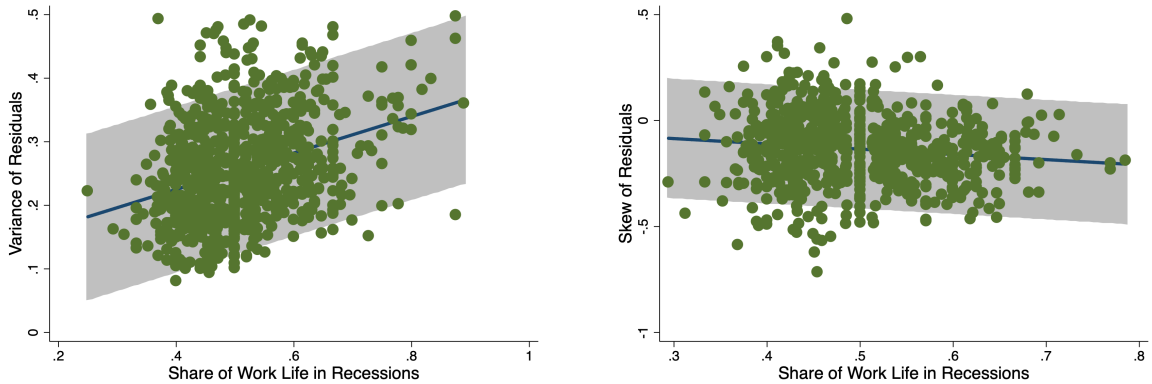
[6] As we show below, our estimates of $\sigma_\alpha^2 + \sigma_\varepsilon^2$ are close to what Storesletten, Telmer and Yaron (2004) report.

[7] This amounts to $37 \times 38 = 1,406$ moment conditions.

[8] Precise distribution of ages across 4 groups is as follows: group $h = 25$ contains ages 23-29, group $h = 35$ contains ages 30-39, group $h = 45$ encompasses ages $40 - 49$, and group $h = 55$ aggregates the remaining ages 50-60.

[9] Busch and Ludwig (2016) are able to use more age groups since the cross-section is larger in their dataset.

Figure 1: Illustration of Accumulation Argument



(A) Variance of residuals (B) Skew of residuals

Notes: Figure 1 is based on PSID Family Files over the period 1978-2014. Panel A plots the variance of residuals $\hat{u}$ for each (age, year)-bin against the share of working life spent in recessions. Panel B plots the skewness of residuals. Grey areas are 90% confidence bands.

The basic idea behind the entire approach is to exploit how the distribution of persistent idiosyncratic shocks accumulates over time: if the income process is persistent (values of ρ are close to 1 in Equation (2)), then as a cohort ages, the cross-sectional income distribution at any age becomes a function of the sequence of shocks experienced by the cohort's members. If the variance of income shocks is higher in recessionary years than in expansionary ones, then a cohort that lived through more contractions will have a higher income variance at a given age than a cohort of the same age that lived through fewer contractions. Panel A in Figure 1 illustrates this intuition: it shows that the cross-sectional variance of $\hat{u}$ tends to increase as the share of labor market life spent in recessions rises. Each green dot corresponds to the variance of $\hat{u}$ computed across households from the same cohort; the location of dots along the horizontal axis is determined by the share of working life a particular cohort spent in recessionary years. Figure A.3 in Appendix A.3 confirms that the aforementioned upward sloping relationship is present in all 4 age groups considered, with a somewhat more pronounced pattern for older groups.

Our extension of that approach in Section 5.3 is based on the insight that a similar "accumulation" argument holds for skewness. If the probability of a large positive income shock is lower during an aggregate contraction, then the skewness of the shock in a recessionary period will be smaller (more negative) than in an expansion. Therefore, by way of comparing two cohorts of the same age, the distribution of residual income for the cohort that lived through more recessions will exhibit a smaller (more negative) cross-sectional skewness. Panel B in Figure 1 illustrates this logic: the skewness of income shocks decreases as the share of labor market life spent in recessions rises. Figure A.4 in Appendix A.4 additionally shows that this negative pattern is present in all 4 age groups and is more pronounced for mature workers (ages 50-60).

4 Volatility of Idiosyncratic Labor Income Risk

In this section, we study how the variance of labor income risk fluctuates across economic expansions and contractions. Conceptually, our exercise is reminiscent of Storesletten, Telmer and Yaron (2004) in that we estimate the same parameters using the same moment conditions, but we diverge from them in that we explore the nature of fluctuations in riskiness of multiple income definitions (Storesletten, Telmer and Yaron (2004) use joint labor income *after* transfers but *before* tax). Following a large literature on income risk, in particular, Guvenen, Ozkan and Song (2014), we also analyze the narrowly defined individual labor income.

By studying different types of labor income, we are able to shed more light on the origins of income risk fluctuations. For example, by moving from hourly wage to head's labor income, we can speak to the quantitative importance of hours (including both intensive and extensive, i.e., employment and unemployment, adjustments) in shaping labor income risk. The intra-family insurance channel can be evaluated through the juxtaposition of risk between head's and joint (head and wife) labor incomes. Finally, in order to quantify the role of government policy — including both taxes and transfers — in possibly alleviating the cyclicality of labor income risk, we assess to what extent (pre-government) joint labor income is more volatile than post-government income.

We first conduct a graphical analysis in Section 4.1 before providing the estimates in Section 4.2. In Section 4.3, we look at subgroups, in particular, the young and the old.

4.1 Graphical Analysis

In order to shed light on the (counter)cyclical nature of idiosyncratic income shock volatility, first we need to obtain the residuals u_{it}^h. We estimate Equation (1) by running a pooled regression (we also experimented with estimating a panel regression, but the results did not change significantly).

We consider the following specification of function $g(\cdot)$:

$$g(x_{it}^h, Y_t) = \theta_0 + \theta_1' D(Y_t) + \theta_2' x_{it}^h + \theta_3' f(x_{it}^h, Y_t),$$

where x_{it}^h includes the following list of observables: cubic polynomial in age, education of head, and the size of the family. Aggregate effects are absorbed in two ways: first, we include a full set of year dummy-variables $D(Y_t)$. Second, we allow for educational premium to vary over the business cycle, and therefore include a quadratic (in education) polynomial $f(\cdot)$:

$$f(x_{it}^h, Y_t) = D(Y_t) \times (\text{Education}_{it}^h + [\text{Education}_{it}^h]^2).$$

Results in Table 2 are consistent with a wide body of literature: the earnings age profile is concave and increasing in education, and large family sizes are associated with high labor income. All estimates are statistically significant and have the expected sign.

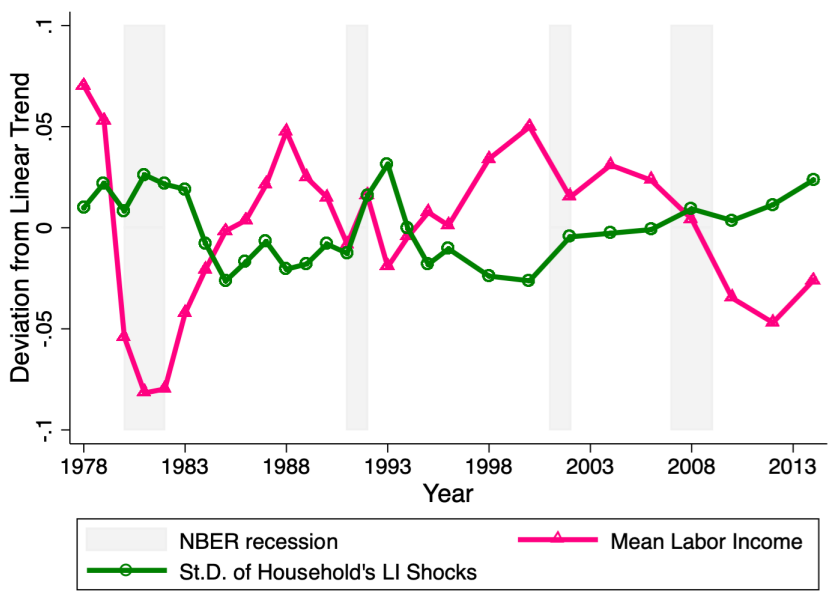
We subsequently retrieve $\hat{u}_{it}^h$ as residuals from the estimated Equation (1). Figure 2, which is close to Figure 1(d) in Storesletten, Telmer and Yaron (2004), plots the evolution of the cross-sectional mean of log (post-government) joint labor income and the standard

Table 2: Estimation of Equation 1

	Dependent variable $\log(y_{it})$				
	Wage	Head's LI	Head's LI (narrow)	Joint LI	Post-govt LI
Age	0.136	0.168	0.186	0.186	0.191
	(0.013)	(0.016)	(0.014)	(0.015)	(0.012)
Age^2	-0.003	-0.003	-0.004	-0.004	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age^3	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.052	0.057	0.057	0.063	0.049
	(0.005)	(0.007)	(0.006)	(0.006)	(0.005)
Family size	0.041	0.067	0.065	0.122	0.113
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	53,210	55,209	54,840	55,209	55,209
Adj. R^2	0.14	0.12	0.14	0.16	0.21

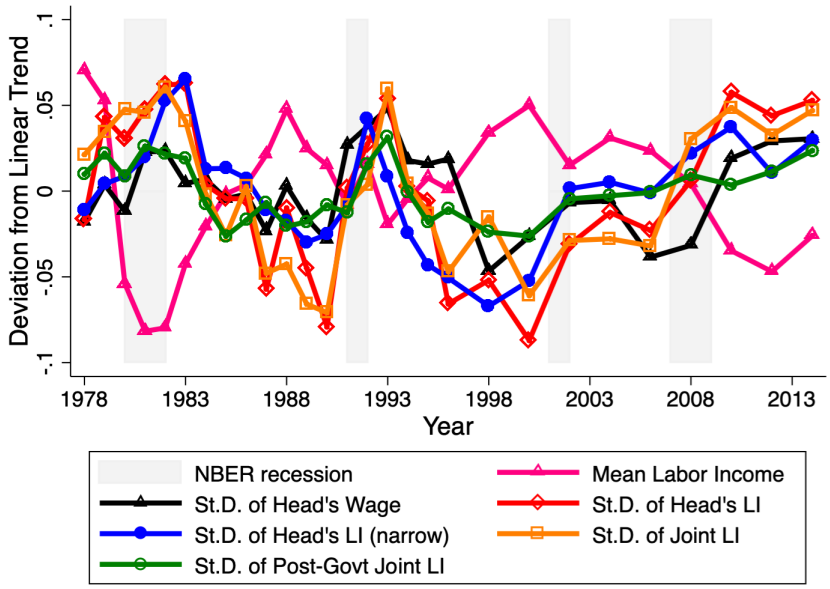
Notes: Table 2 reports the results of OLS estimations, and is based on Family Files from PSID over the period 1978-2014. `Age` is the age of a household's head, and `Education` is a number of completed (by the head) years of college. Standard errors are in parentheses. Regressions also include yearly dummies and a time-dependent educational premium (not reported). All reported coefficients are significant at the 1% level.

Figure 2: Mean Log Earnings and Standard Deviation of $\hat{u}_{it}^h$



Notes: Figure 2 is based on Family Files from PSID over the period 1978-2014. The mean labor income in year t is a cross-sectional mean of log (post-government) joint labor income in a corresponding year. The standard deviation of joint labor income shocks in year t is a cross-sectional standard deviation of $\hat{u}_{it}^h$ - residuals from the estimated Equation (1). We also subtract linear trends from the series, which chiefly eliminates the long-run mean (the slope coefficient is nearly zero). Grey bars represent NBER recessions.

Figure 3: Standard Deviation of Idiosyncratic Income Component



Notes: Figure 3 is based on Family Files from PSID over the period 1978-2014. The mean labor income in year t is a cross-sectional mean of log post-government joint labor income in a corresponding year. The standard deviation of labor income shocks in year t is a cross-sectional standard deviation of $\hat{u}_{it}^h$ -residuals from the estimated Equation (1), where the left-hand side variable is one from the set $y_{it} \in$ {head's wage, head's income, head's income (narrow), joint labor income, post-government joint labor income}. We also demean the resulting series. Grey bars represent NBER recessions.

deviation of $\hat{u}_{it}^h$.[10] The figure displays a robust feature of the data: the standard deviation of joint labor income shocks is countercyclical, decreasing in expansions and increasing in recessions. The labor income risk increases during all NBER recession years within the sample period: 1980-1981, 1991, 2001, and 2007-2009.

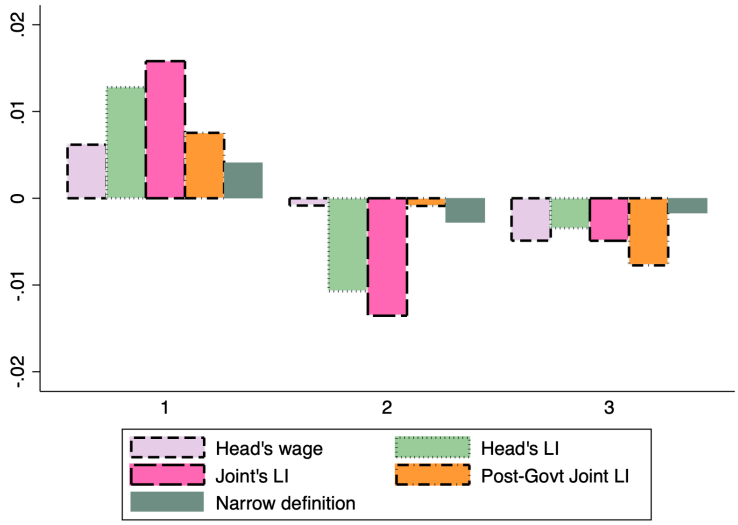
While Figure 2 indicates that the countercyclical income risk is a robust feature of the data, it does not say much about where this cyclicality originates. This motivates us to repeat the exercise for other income definitions (Figure 3).

A visual inspection of Figure 3 suggests that the countercyclical nature of income risk is not an artifact of the post-government joint labor income: all five series appear to be negatively correlated with mean income. One can also notice that despite exhibiting similar dynamics, there is a visibly pronounced heterogeneity in fluctuation of risk across income types. For example, head's labor income and (pre-government) joint labor income (the red and orange lines, respectively) track each other fairly closely, while the line corresponding to the post-government joint labor income is visually twice less volatile.

While Figure 3 is suggestive, it is barely useful to compare how the countercyclicality of different income definitions relate to each other. We, therefore, categorize every sample year into one of 3 bins, depending on the growth rate of real GNP per capita in that year: if GNP per capita grew by a lot (in the top tertile of the growth rate distribution), we place

[10] The main difference is that, while Storesletten, Telmer and Yaron (2004) use the joint labor income plus government transfers and do not subtract taxes, we take into account both government transfers and taxes.

Figure 4: Volatility of Idiosyncratic Income Risk by GNP per Capita Growth Tertile



Notes: Figure 4 is based on Family Files from PSID over the period 1978-2014. Each year from the period 1978-2014 is classified in one out of 3 bins, depending on which tertile the growth rate of GNP per capita in that year falls into. Tertile 1 contains years with the lowest growth rate of GNP per capita, while tertile 3 contains years with the highest growth rates. The standard deviations shown are averages over years in the bin. Each tertile contains standard deviations for 5 measures of labor income: head's wage, head's labor income, joint labor income, post-government joint labor income, and head's labor income (narrow definition).

that year in bin 3. Conversely, if the growth was in a bottom tertile of the growth rate distribution, that year falls in bin 1. Table 3 reports the mean and median GNP growth rate for each tertile. Subsequently, we take the average (across years that are sorted in a particular bin) deviation of a corresponding statistic from its long-run mean and do it for all 5 different income definitions (Figure 4).

Figure 4 anticipates several findings. At the very least, it reiterates the message of Figure 3: the volatility of income shocks exhibits countercyclicality, and this pattern is robust across different labor income definitions. However, we can say more than that. First, consistently with findings of Guvenen, Ozkan and Song (2014), the narrowly-defined head's labor income exhibits relatively modest fluctuations in risk over the cycle. Second, head's wages are less volatile and less cyclical than head's labor income, pointing at the importance of hours in driving the labor income risk fluctuations. Third, joint labor income, if anything, exhibits fluctuations in income risk that are comparable to those of the head's labor income. And, finally, post-government income risk fluctuations are moderate, quantitatively similar to those of the narrowly-defined individual labor income.

Table 4: GMM Estimation Results: Time-Varying Volatility Only

Type of Income	ρ	σ_E	σ_C	$\sqrt{\sigma_\alpha^2 + \sigma_\varepsilon^2}$	$\sigma_C - \sigma_E$
Head Hourly Wage	0.91	0.10	0.15	0.69	0.05
	(0.00)	(0.01)	(0.01)	(0.01)	
Head Labor Income	0.84	0.11	0.20	0.79	0.09
	(0.01)	(0.01)	(0.01)	(0.01)	
Head LI (narrow definition)	0.84	0.11	0.15	0.76	0.04
	(0.00)	(0.01)	(0.01)	(0.01)	
Joint (Head+Wife) LI	0.77	0.16	0.23	0.78	0.07
	(0.01)	(0.03)	(0.02)	(0.03)	
Post-Govt Joint LI	0.81	0.09	0.14	0.69	0.05
	(0.01)	(0.03)	(0.01)	(0.01)	

Notes: Table 4 reports the estimation results for Θ by GMM based on the moment conditions of type (5). Standard errors are in parentheses.

Table 3: Mean and Median GNP per Capita Growth Rate in Each Bin

	Tertile 1	Tertile 2	Tertile 3
Mean growth rate, %	-1.2	1.5	3.2
Median growth rate, %	-1.0	1.5	2.7

Notes: Table 3 reports the mean and median for each tertile of the distribution of GNP per capita growth rates.

These cyclical properties we observe are robust to alternative definitions of the business cycle. In Appendix B, we provide analogous figures where we categorize years based on the NBER definition of recessions (B.1) and by mean income growth rate (Section B.2).

4.2 Estimation Results

In Section 4.1, we provided suggestive evidence on the countercyclical nature of income shocks volatility. In this section, we take a step forward and estimate the vector of structural parameters that govern the income process (2). As it has been discussed above, there are in total $H \times T$ moment conditions of type (5). In Section 3 we argued that we cannot use all of them, as the sample size of certain age-year cells becomes too small to obtain precise estimates. Instead, we focus on a subset of moment conditions that correspond to ages 25, 35, 45 and 55. We check that there are at least 100 observations in each cell.

Our baseline business cycle indicator is based on real GNP per capita. That is, we set $I_t = 1$ if in year t real GNP per capita growth rate exceeded the sample mean and assign $I_t = 0$ otherwise (Appendix A.5 compares the allocation of sample years into "expansions" and "contractions" based on alternative aggregate measures).

Table 4 provides GMM estimates for all 5 income definitions. Our results reconcile the findings of previous studies with seemingly contradicting results. On one hand, post-government joint labor income exhibits a sizable countercyclical risk. Specifically, the estimated standard deviation is 0.09 in expansions and 0.14 in recessions. The ratio of our

estimates (0.14/0.09=1.56) is somewhat lower than what Storesletten, Telmer and Yaron (2004) report (0.162/0.088=1.84), but still within the range of estimates they provide. This small difference might arise because of taxes: the Storesletten, Telmer and Yaron (2004) definition of labor income corresponds to joint labor income *after* government transfers but *before* taxes, while we incorporate both types of government redistribution policies. Consistent with our conjecture, Heathcote, Perri and Violante (2010a) study the distributional effects of taxes and transfers and find that they compress the earnings inequality, especially at the bottom of the distribution.

On the other hand, although the narrowly-defined head's labor income also exhibits countercyclical variance, its countercyclicality is noticeably weaker than that of head's labor income. The ratio of the standard deviation in recessions and that in expansions is 1.36. Guvenen, Ozkan and Song (2014) find that the second moment of income risk is flat with respect to the business cycle, while our findings suggest moderate countercyclical fluctuations. This difference might arise from several sources, including the way we identified the income shock (residual from OLS regression, rather than income growth), the estimation approach (parametric, rather than non-parametric), and different data used (PSID vs. Social Security Administration records).

Head's labor income risk shows the greatest countercyclicality, with the recessionary standard deviation being almost twice as large as the expansionary one. Wage rate does not show such a pronounced countercyclicality, hinting at an important quantitative role of hours (most likely, employment and unemployment). This finding mirrors the observation from Figure 4. Moving from head's labor income to joint labor income, we see that intra-family insurance channel through an added worker effect reduces fluctuation in risk from 0.09 down to 0.07. The limited quantitative role of this channel could also have been anticipated from Figure 4. Finally, the taxes and transfers by the government further mitigate fluctuations in risk, from 0.07 to 0.05.

4.3 Analysis of Subgroups

We further break down the sample into 2 subgroups — "young" (ages 22-39) and "old" (ages 40-60) — and re-estimate the parameters on those subsamples in order to uncover heterogeneity between the age groups (see Table 5). The column "overall" corresponds to the case when we estimate the parameters without allowing for the time-varying volatility. While the "overall" estimates of volatility for an old subsample are higher than the ones for a young subsample (by a factor of 2-3 for head's hourly wage and head's labor income), it appears that a big portion of business cycle fluctuations in risk comes from young households: the distance between $\hat{\sigma}_E$ and $\hat{\sigma}_C$ is substantially higher in the young subsample. On the other hand, households aged 40-60 exhibit muted countercyclicality in income risk across all 5 income definitions.

5 Skewness of Idiosyncratic Labor Income Risk

In this section, we extend our analysis to allow for a time-varying skewness of income shocks. While countercyclical variance can tell us that tail events (large positive and negative shock

Table 5: GMM Estimates of Earnings Shock Volatility By Age Group

Households Age 22-39				
	Overall	Exp	Rec	Diff
Head Hourly Wage	0.09	0.06	0.15	0.09
	(0.02)	(0.02)	(0.02)	
Head Labor Income	0.12	0.09	0.21	0.12
	(0.03)	(0.04)	(0.02)	
Head LI (narrow definition)	0.10	0.06	0.11	0.06
	(0.02)	(0.02)	(0.03)	
Joint (Head+Wife) LI	0.12	0.08	0.18	0.10
	(0.03)	(0.03)	(0.04)	
Post-Govt Joint LI	0.14	0.02	0.16	0.14
	(0.02)	(0.01)	(0.06)	
Households Age 40-60				
	Overall	Exp	Rec	Diff
Head Hourly Wage	0.26	0.26	0.28	0.02
	(0.06)	(0.06)	(0.07)	
Head Labor Income	0.22	0.22	0.26	0.04
	(0.05)	(0.06)	(0.06)	
Head LI (narrow definition)	0.21	0.22	0.25	0.05
	(0.08)	(0.09)	(0.09)	
Joint (Head+Wife) LI	0.15	0.13	0.21	0.08
	(0.05)	(0.05)	(0.04)	
Post-Govt Joint LI	0.13	0.11	0.17	0.06
	(0.02)	(0.02)	(0.01)	

Notes: Table 5 is based on PSID Family Files over the period 1978-2014. The top part of the table corresponds to the "young" subsample (22-39 years old) and the bottom part to the "old" subsample (40-60 years old). "Overall" columns contain estimates when σ_t is assumed to be time-invariant. "Diff" column contains the distance between estimates of σ_E and σ_R. Standard errors are in parentheses.

realizations) become more likely during economic downturns, there is a growing body of literature highlighting the importance of the third moment (*inter alia,* Bloom, Guvenen and Salgado, 2016; Guvenen, Ozkan and Song, 2014; Busch, Domeij, Guvenen and Madera, 2018)). Non-zero skewness implies that some extreme shock realizations are likely to be either positive or negative — depending on the sign of the coefficient of skewness. This also implies that constant skewness — something our analysis has implicitly assumed so far — can mask a rich heterogeneity between left- and right-tail events. We proceed in the same way as in the previous section on the cyclicality of variance. In Section 5.1, we first graphically confirm that these phenomena are present in our dataset. In Section 5.2, we employ an alternative way to measure income shocks, used by Guvenen, Ozkan and Song (2014), to further facilitate the comparison between our findings and theirs. Finally, in Section 5.3, we explore the quantitative magnitude of skewness fluctuations over the business cycle for all 5 different income definitions.

5.1 Graphical Analysis

Throughout our analysis of skewness, we consider the following 2 conventional measures:

1. third central moment:

$$\text{Third moment}_t = \frac{1}{n_t}\sum_i (\hat{u}_{it}^h - \bar{\hat{u}}_{it}^h)^3,$$

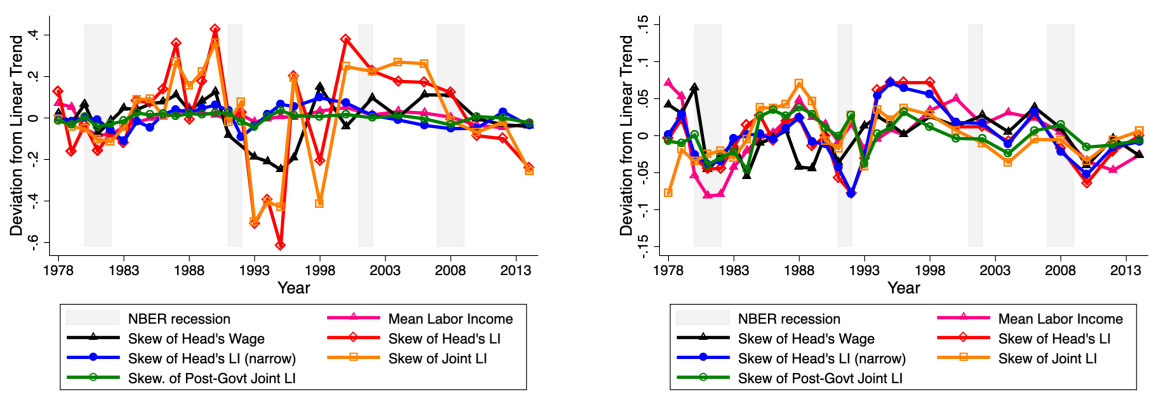
2. Kelly's measure:

$$\text{Kelly}_t = \frac{(P90_t - P50_t) - (P50_t - P10_t)}{P90_t - P10_t}.$$

The interpretation of these statistics is straightforward. The first one is a sample analogue of the third central moment, which is a measure of skewness by definition. The second (the Kelly's measure) is a function of several percentiles of $\hat{u}_{it}^h$-distribution, which makes it robust to "extreme" observations (note that it is independent from the first and last deciles of the underlying distribution). Intuitively, the Kelly's measure computes the difference in inequality between the right ($P90 - P50$) and left ($P50 - P10$) tails, and relates it to the overall variation in the sample ($P90 - P10$). If the right tail is heavier than the left one (underlying distribution of $\hat{u}_{it}^h$ has a positive skew), then the Kelly's measure is positive. And the other way around, a heavier left tail makes the Kelly's measure negative.

Procyclical skewness implies that during economic upturns (downturns), the right (left) tail of income shocks thickens, leading to a disproportionate bigger fraction of large positive (negative) shocks. At the same time, the odds of receiving a large negative (positive) shock go down.

Figure 5: Skew of Idiosyncratic Labor Income Risk, by GNP per Capita Growth Quantile



(A) Third central moment (B) Kelly's measure

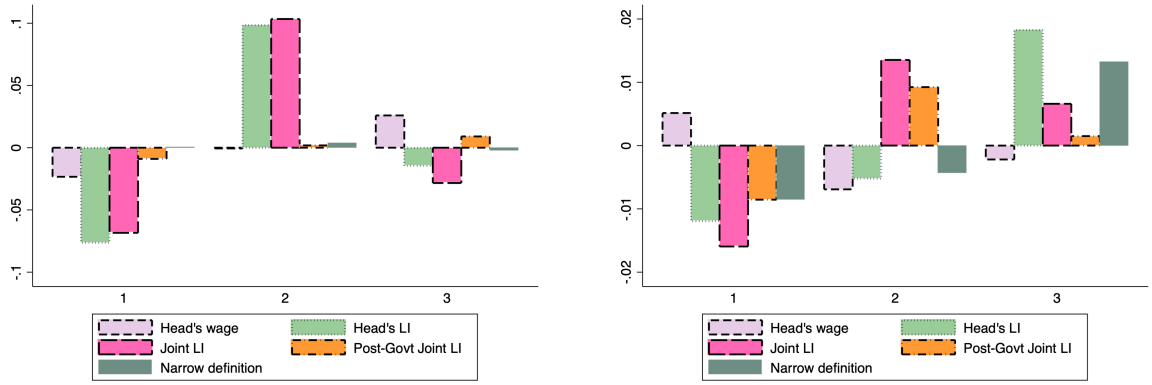
Notes: Figure 5 is based on PSID Family Files over the period 1978-2014. Panel A plots the third central moment, Panel B plots the Kelly's measure.

Figure 5 illustrates the evolution of two measures of skewness over the sample period: Panel A plots the third central moment, while Panel B plots the Kelly's measure. Several

observations are in order. First, both measures of skewness are procyclical, increasing in expansions and decreasing in contractions. Second, the third moment is a more volatile measure of skewness as compared with the Kelly's measure — something one could have anticipated, given that the Kelly's measure is robust to outliers. Panel A of Figure 5 shows that the skewness of head's and joint labor incomes fluctuates the most across income definitions we consider. This implies, for example, that probabilities of tail events co-move very strongly with aggregate conditions for these income types. The remaining definitions also exhibit procyclical skewness, but movements in probability of their tail events are weaker.

In order to better understand which income definitions exhibit stronger/weaker cyclicality of skewness, in Figure 6 we plot the average (deviation from the trend of) skewness of income shocks for expansions and contractions defined using GNP per capita growth tertile. Panel A plots the third central moment, while Panel B plots the Kelly's measure. The figure confirms that the skewness is procyclical, with the Kelly's measure exhibiting a stronger pattern. That means that during economic downturns, a large negative income shock is more likely than a large positive one.

Figure 6: Skew of Idiosyncratic Labor Income Risk, by GNP per Capita Growth Tertile



(A) Third central moment (B) Kelly measure

Notes: Figure 6 is based on PSID Family Files over the period 1978-2014. Panel A plots the third central moment, Panel B plots the Kelly's measure. Each year from the period 1978-2014 is classified in one out of 3 bins, depending on which tertile the growth rate of GNP per capita in that year falls into. Tertile 1 contains years with the lowest growth rate of GNP per capita, while tertile 3 contains years with the highest growth rates. The measures of skewness shown are averages over years in the bin. Each tertile contains skewness measures for 5 different types of labor income: head's wage, head's labor income, joint labor income, post-government joint labor income and head's labor income (narrow definition).

A closer inspection of Figure 6 reveals that the skewness of post-government joint labor income barely changes over the cycle. It implies that the odds of getting a very negative shock for that income definition co-move with the odds of getting a very positive shock. Interestingly, both measures of skewness rank post-government income as the one with the most stable skewness.

When we look at household's income without transfers and taxes (joint labor income), we find that the cyclicality of skewness becomes stronger: the probability of getting a large

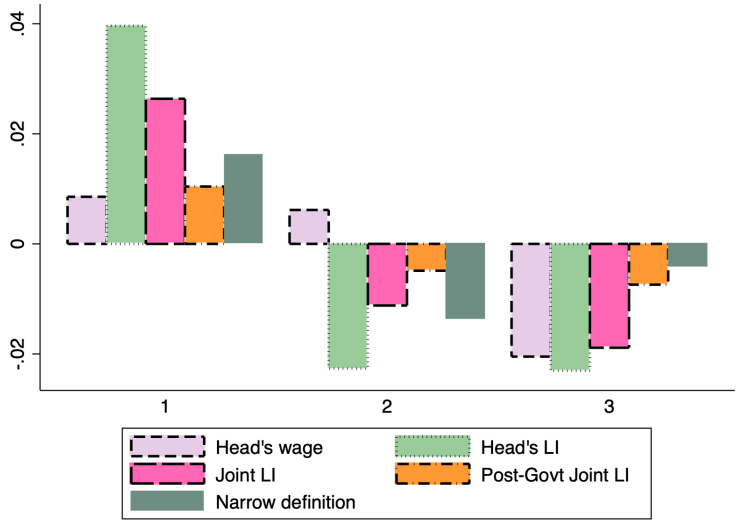
negative income shock increases by more than the odds of getting a large positive shock during economic contractions. This observation can be interpreted as evidence of the insurance or stabilizing role of the government.

Head's labor income exhibits the strongest fluctuations in skewness. This observation might reflect intra-family insurance through an added worker effect: during economic downturns the probability of getting laid off increases, and the wife can step in and compensate for the head's job loss (by working more hours, getting an extra job, etc.). The head's wage exhibits relatively moderate fluctuations in skewness (the Kelly's measure is even countercyclical). The narrowly defined labor income shows shifts in skewness that are quantitatively comparable with those of the household's income.

Figures A.6 and A.8 in Appendix B display similar patterns and confirm that the above observations are robust to alternative ways of business cycle identification.

5.2 Labor Income Risk as in Guvenen, Ozkan and Song (2014)

Figure 7: Labor Income Risk as in Guvenen et al. (2014): Volatility of Labor Income Risk by GNP per Capita Growth Quantile

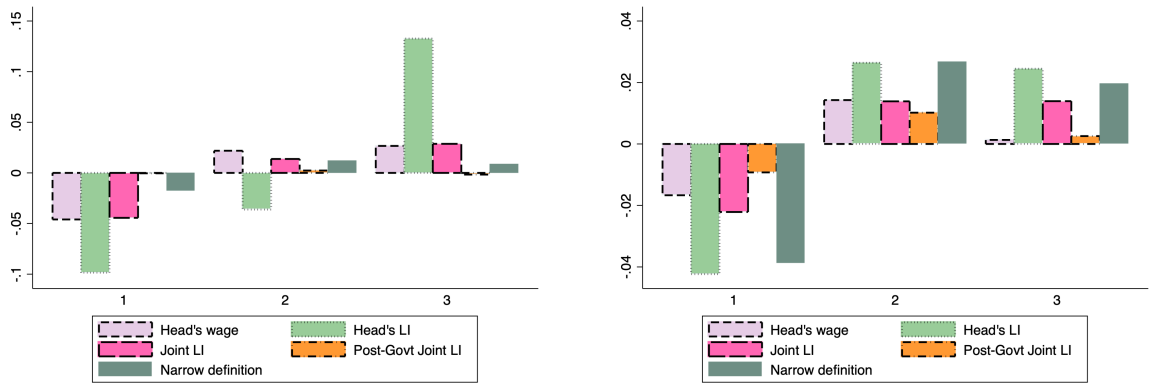


Notes: Figure 7 is based on Family Files from PSID over the period 1978-2014. Each year from the period 1978-2014 is classified in one out of 3 bins, depending on which tertile the growth rate of GNP per capita in that year falls into. Tertile 1 contains years with the lowest growth rate of GNP per capita, while tertile 3 contains years with the highest growth rates. The standard deviations shown are averages over years in the bin. Each tertile contains standard deviations for 5 measures of labor income: head's wage, head's labor income, joint labor income, post-government joint labor income, and head's labor income (narrow definition).

This section explores the cyclical nature of shocks when those are identified as the growth rate of income (Guvenen, Ozkan and Song, 2014; Busch, Domeij, Guvenen and Madera, 2018). Their approach is non-parametric and allows to study fluctuations in risk with few

identifying assumptions.[11] While in this paper we opt to follow Storesletten, Telmer and Yaron (2004) and use the parametric approach given the size and changing frequency of the dataset, it is important to establish the connection between these two approaches. Taking into account the fact that PSID became biannual starting from 1996, we take the 2-year growth rate as our alternative measure of income shocks.[12]

Figure 8: Labor Income Risk as in Guvenen et al. (2014): Skewness of Labor Income Risk, by GNP per capita Growth Quantile



(A) Third central moment (B) Kelly measure

Notes: Figure 8 is based on PSID Family Files over the period 1978-2014. Panel A plots the third central moment, while Panel B plots the Kelly's measure. Each year from the period 1978-2014 is classified in one out of 3 bins, depending on which tertile the growth rate of GNP per capita in that year falls into. Tertile 1 contains years with the lowest growth rate of GNP per capita, while tertile 3 contains years with the highest growth rates. The measures of skewness shown are averages over years in the bin. Each tertile contains skewness measures for 5 different types of labor income: head's wage, head's labor income, joint labor income, post-government joint labor income and head's labor income (narrow definition).

First, regarding the cyclical nature of the volatility of idiosyncratic labor income risk, Figure 7 shows that the countercyclicality of the volatility carries over to this alternative way of shock identification. The volatility of labor income risk measure in the same way as in Guvenen, Ozkan and Song (2014) is highest when GNP per capita growth is in the lowest quantile, and is lower when the growth rate is higher. Comparing 5 definitions of labor income, head's labor income exhibits the strongest cyclical movement of volatility, while narrowly-defined head's labor income generally exhibits weaker cyclicality than head's labor income. This is consistent with our benchmark result using the parametric approach. Moreover, post-government joint labor income exhibits little cyclicality, especially when compared with the sizable cyclicality of individual labor income. This indicates the role of public insurance in lowering income volatility.

Second, Figure 8 confirms that procyclicality of skewness, measured as the third central moment (Panel (A)) or the Kelly's measure (Panel (B)), is also preserved when shocks are

[11] Guvenen, Ozkan and Song (2014) differentiate between transitory and persistent components of income. The *transitory* component is measured as 1-year growth rate ($\log(y_{it}) - \log(y_{it-1})$). The *persistent* component is a 5-year growth rate ($\log(y_{it}) - \log(y_{it-5})$).

[12] Busch, Domeij, Guvenen and Madera (2018), who also use the PSID, use the 1-year growth rate before 1996 and the 2-year growth rate starting from 1996 to measure income shocks.

measured by growth rates of income. Both measures of skewness exhibit strong procyclicality, declining sharply during contractions. Overall, our key qualitative results are robust to the non-parametric way of income risk measurement; for various definitions of labor income, variance of income risk is countercyclical, while skewness is procyclical, but the cyclicality of variance is dampened when labor income is narrowly defined.

5.3 Joint Estimation of Cyclical Volatility and Skewness

The objective of this subsection is to jointly estimate both the volatility (second moment) and skewness (third moment) of income shocks. Technically, we still assume that the labor income shock follows process (2), but innovations to a persistent component η_{it} are now drawn from a *skew normal distribution*, which is a generalization of a normal distribution to the case with a non-zero skewness. The skew normal distribution is a family of probability distributions governed by 3 parameters: location ($\zeta \in \mathbb{R}$), scale ($\omega \in \mathbb{R}_{++}$), and shape ($\nu \in \mathbb{R}$).[13] Innovations to the persistent component are now assumed to be drawn from the distribution:

$$\eta_{it} \sim \mathcal{SN}(\zeta, \omega_t, \nu_t). \tag{6}$$

We assume that the location parameter is business cycle invariant, and we normalize it to 0. Figure 9 shows how the shape parameter ν governs the third moment of the skew normal distribution: the corresponding density tends to be skewed towards more positive values (positive skew) for positive ν and towards negative values (negative skew) for negative values of ν. The shape parameter ω is set equal to 0.1 across all 5 shown densities.

Crucially, we make variance and skewness state-dependent, allowing the shock structure to change between expansions and contractions. The support of both ω_t and ν_t consists of two points:

$$\omega_t = \begin{cases} \omega_E \text{ if expansion at } t \\ \omega_C \text{ if contraction at } t \end{cases}$$

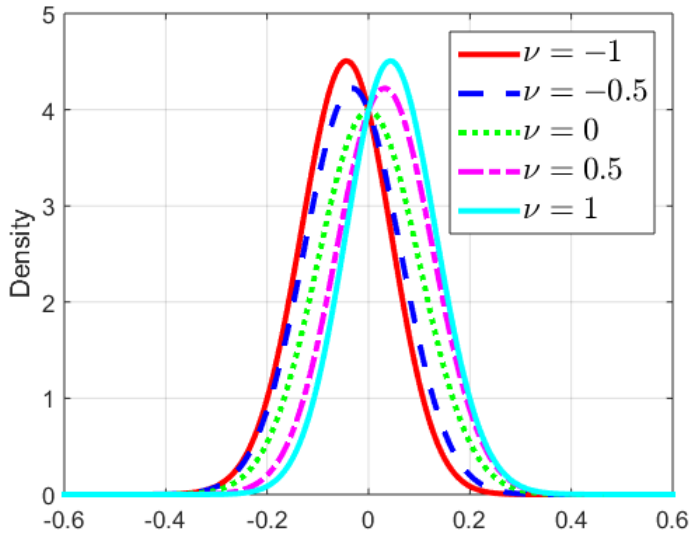
and

$$\nu_t = \begin{cases} \nu_E \text{ if expansion at } t \\ \nu_C \text{ if contraction at } t. \end{cases}$$

Next, we estimate a set of 6 parameters jointly. First, analogously to the case with a state-dependent volatility, it is straightforward to show that the following $H \times T$ moment

[13] The p.d.f. of the skew normal distribution is $f(x) = 2\phi(x)\Phi(\nu x)$, where $\phi(x)$ and $\Phi(x)$ are p.d.f. and c.d.f. of the standard normal distribution, respectively. In case of symmetric distribution ($\nu = 0$), the formula collapses to a standard normal p.d.f.

Figure 9: Skew Normal Density for Different Values of ν



Notes: Figure 9 plots the skew normal density for 5 values of $\nu \in \{-1, -0.5, 0, 0.5, 1\}$. The shape parameter ω is 0.1 and location parameter ζ is set to 0.

conditions must be satisfied:[14]

$$\mathbb{E}_t\left[(u_{it}^h)^2 - \sigma_\alpha^2 - \sigma_\varepsilon^2 - \sum_{j=0}^{h-1}\rho^{2j}\left\{I_{t-j}\left(\omega_E^2\left[1-\frac{2\delta_E^2}{\pi}\right]\right) + (1-I_{t-j})\left(\omega_C^2\left[1-\frac{2\delta_C^2}{\pi}\right]\right)\right\}\right] = 0, \tag{7}$$

where $\delta_i = \frac{\nu_i}{\sqrt{1+\nu_i^2}}$ and $i \in \{E, C\}$.

We use a set of extra $H \times T$ moment conditions (in addition to moments of type (7)), in order to identify the parameters ν_E and ν_C by way of relating empirical skewness to theoretical one:

$$\mathbb{E}_t\left[\text{skew}(u_{it}^h) - \underbrace{\text{skew}(\sigma_\alpha^2 + \sigma_\varepsilon^2)}_{=0} - \sum_{j=0}^{h-1}\rho^{3j}\left\{I_{t-j}\gamma_E + (1-I_{t-j})\gamma_C\right\}\right] = 0, \tag{8}$$

where $\gamma_i = \frac{4-\pi}{2}\frac{\left(\delta_i\sqrt{2/\pi}\right)^3}{\left(1-2\delta_i^2/\pi\right)^{\frac{3}{2}}}$ and $i \in \{E, C\}$.

In total, we have $2 \times H \times T$ moment conditions to estimate the following 7 parameters: $\rho, \omega_E, \omega_C, \delta_E, \delta_C, \sigma_\alpha, \sigma_\varepsilon$. Similarly to the case with time-varying variance only (Section 4), we do not estimate σ_α and σ_ε separately but only their sum.[15] That makes the number of

[14] If a random variable $Y \sim \mathcal{SN}(\zeta, \omega, \nu)$ has a skewed normal distribution, then $\mathbb{E}[Y] = \zeta + \omega\delta\sqrt{\frac{2}{\pi}}$ and $\text{Var}[Y] = \omega^2\left(1 - \frac{2\delta^2}{\pi}\right)$, where $\delta = \frac{\nu}{\sqrt{1+\nu^2}}$. Skewness can then be expressed as $\gamma = \frac{4-\pi}{2}\frac{\left(\delta\sqrt{2/\pi}\right)^3}{(1-2\delta^2/\pi)^{\frac{3}{2}}}$.

[15] Even though we do not estimate these parameters separately, we still confirm in Table 6 that their sum is close to what Storesletten, Telmer and Yaron (2004) report.

parameters to be estimated 6.

Table 6: GMM Estimation Results: Time-Varying Volatility and Skewness

Type of Income	ω_E	ω_C	δ_E	δ_C	ρ	$\sqrt{\sigma_\alpha^2 + \sigma_\varepsilon^2}$
Head Hourly Wage	0.10	0.17	-0.54	-0.57	0.91	0.69
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Head Labor Income	0.12	0.25	-0.67	-0.70	0.76	0.78
	(0.06)	(0.11)	(0.03)	(0.02)	(0.06)	(0.12)
Head LI (narrow definition)	0.13	0.21	-0.67	-0.70	0.75	0.74
	(0.05)	(0.11)	(0.03)	(0.03)	(0.05)	(0.05)
Joint (Head+Wife) LI	0.16	0.25	-0.56	-0.62	0.86	0.78
	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Post-Govt Joint LI	0.10	0.17	-0.58	-0.64	0.78	0.69
	(0.05)	(0.08)	(0.02)	(0.02)	(0.04)	(0.03)

Notes: Table 6 reports the estimation results for Θ by GMM based on the moment conditions of type (7) and (8). Standard errors are in parentheses.

Table 6 reports the parameter estimates for 5 definitions of labor income. Note, however, that parameters governing the skew normal distribution do not map one-to-one to parameters of the normal distribution: for example, the variance is now a function of both ω and δ (see Footnote 14). We, therefore, report in Table 7 the variance and skewness for all 5 income definitions that are implied by the parameter estimates shown in Table 6.

Let us start with volatility of labor income risk implied by the estimated parameters. We are interested in seeing how consistent they are with respect to our results from Section 4.2. Overall, our previous findings remain intact even when we allow for a time-varying skewness. We find that the implied estimates of volatility are close to what we reported when allowed for a time-varying second moment only (Section 4). This result is not mechanical as the variance is now a function of 2 parameters, of which one affects both the volatility and skewness. We also note that the standard errors in Table 6 became larger, pushing the significance of some of the estimated parameters to borderline values. The persistence parameter ρ is estimated to be somewhat lower than in Table 4; however, given higher standard errors in Table 6, previous estimates are still covered by the 95% confidence interval.

Table 7: GMM-Implied Volatility and Skewness

Type of Income	σ_E	σ_C	skew_E	skew_C	$\Delta\sigma$	Δskew
Head Hourly Wage	0.09	0.15	-0.04	-0.06	0.06	-0.02
Head Labor Income	0.10	0.20	-0.10	-0.13	0.10	-0.03
Head LI (narrow definition)	0.11	0.17	-0.11	-0.13	0.06	-0.02
Joint (Head+Wife) LI	0.14	0.21	-0.05	-0.08	0.07	-0.03
Post-Govt Joint LI	0.09	0.15	-0.06	-0.09	0.06	-0.03

Notes: Table 7 reports the standard deviation and skewness of income shocks implied by GMM estimates from Table 6 using the mapping from parameters into moments from Footnote 14. The last two columns report the differences in the estimated standard deviations and coefficients of skewness across expansions and contractions.

Next, we look at the skewness implied by the estimated parameters. The third and fourth columns of Table 7 show the implied skewness in expansions and recessions, respectively, and the last column shows their difference. Several comments are in order. First, skewness is procyclical (the probability of a large decline increases in recessions) and is estimated to be the highest with head's labor income. Even with the narrower definition of head's labor income, the levels of skewness in both expansions and recessions are not significantly affected, and skewness is equally procyclical in both the normal and narrow definitions of head's labor income. On the other hand, cyclicality of variance is weakened when narrowly-defined head's labor income instead of head's labor income is used. Therefore, it is not surprising that Guvenen, Ozkan and Song (2014) find skewness to be procyclical using the narrow definition of head's labor income, while they find acyclical variance.

Second, the wife's income lowers the level of skewness in both expansions and recessions, but its cyclicality is not significantly affected. Third, incorporating government taxes and transfers does not seem to affect both the level and the cyclicality of skewness of income shocks. Finally, head's hourly wage exhibits the lowest level of skewness, which implies that hours — most likely due to (un)employment — play an important role in shaping the downside risk of income shocks, and its impact is quantitatively similar regardless of the aggregate state.

While we do not see significant heterogeneity in the cyclicality of skewness across different income definitions, it does not imply, however, that the probability of tail events evolves similarly as well. The key reason is that both the volatility and skewness of income shocks simultaneously determine the probability of tail events. In the next section, we explore the implications of the reported estimates and put them into economic context.

6 Economic Interpretation

In this section, we provide economic interpretations for our estimates. First, in Section 6.1, we graphically show how shock distributions change depending on the aggregate economic activity. Second, in Section 6.2, we quantify the probabilities of tail events for different income definitions. Our results will recover a substantial heterogeneity in the probabilities of tail events across income types, despite the fact that parameter estimates might seem similar. Finally, in Section 6.3, we discuss how to interpret the magnitude of cyclical changes in labor income risks.

6.1 Estimated Distributions of Income Shocks

In this subsection, we plot the resulting distribution of shocks η_{it} for the parameter estimates from Table 6. Figure 10 shows the distributions of shocks η_{it} in expansions (solid red lines) and in recessions (dashed blue lines), for 5 labor income definitions. The most striking difference between expansion and contraction distributions of income shocks is observed in the case of the head's labor income (Panel (B)): while the solid red line (expansion) is fairly symmetric around 0 with a small variance, the blue dashed line (contraction) is substantially more dispersed with a heavy left tail. This observation implies that individuals are more likely to be hit by a large negative (rather than positive) shock during economic contractions.

However, when the economy is expanding, tail events, both positive and negative, become almost equally likely, although the overall probability of large shocks becomes smaller.

Panel (A) of Figure 10 confirms again that it is the number of hours worked rather than hourly wages that drives a significant portion of the countercyclicality of head's labor income risk. In particular, we see that the recessionary distribution of wage shocks gets substantially closer to the expansionary one, compared with head's labor income (Panel (B)), even though we still observe a strongly pronounced countercyclicality of wage shocks. We will make this point clear below when we estimate the probabilities of tail events.

Intra-family insurance channels are visible in Panel (D) of Figure 10 — the variance is more stable, and the probability of tail events drops as compared with head's labor income — however, it appears that this channel has a limited quantitative role. Government transfers and taxes (Panel (E)) smooth out countercyclical risk and procyclical skewness significantly, even after the spousal channel is taken into account — this result has been anticipated since Section 4. Finally, labor income risk for people with a strong market attachment (narrow definition) exhibits more moderate swings in volatility and skewness over the cycle, compared with head's labor income (Panels (C) vs. (B)). If anything, the distributions shown in Panel (C) are similar to those in Panel (A) (head's hourly wage).

6.2 Asymmetries in Tail Events

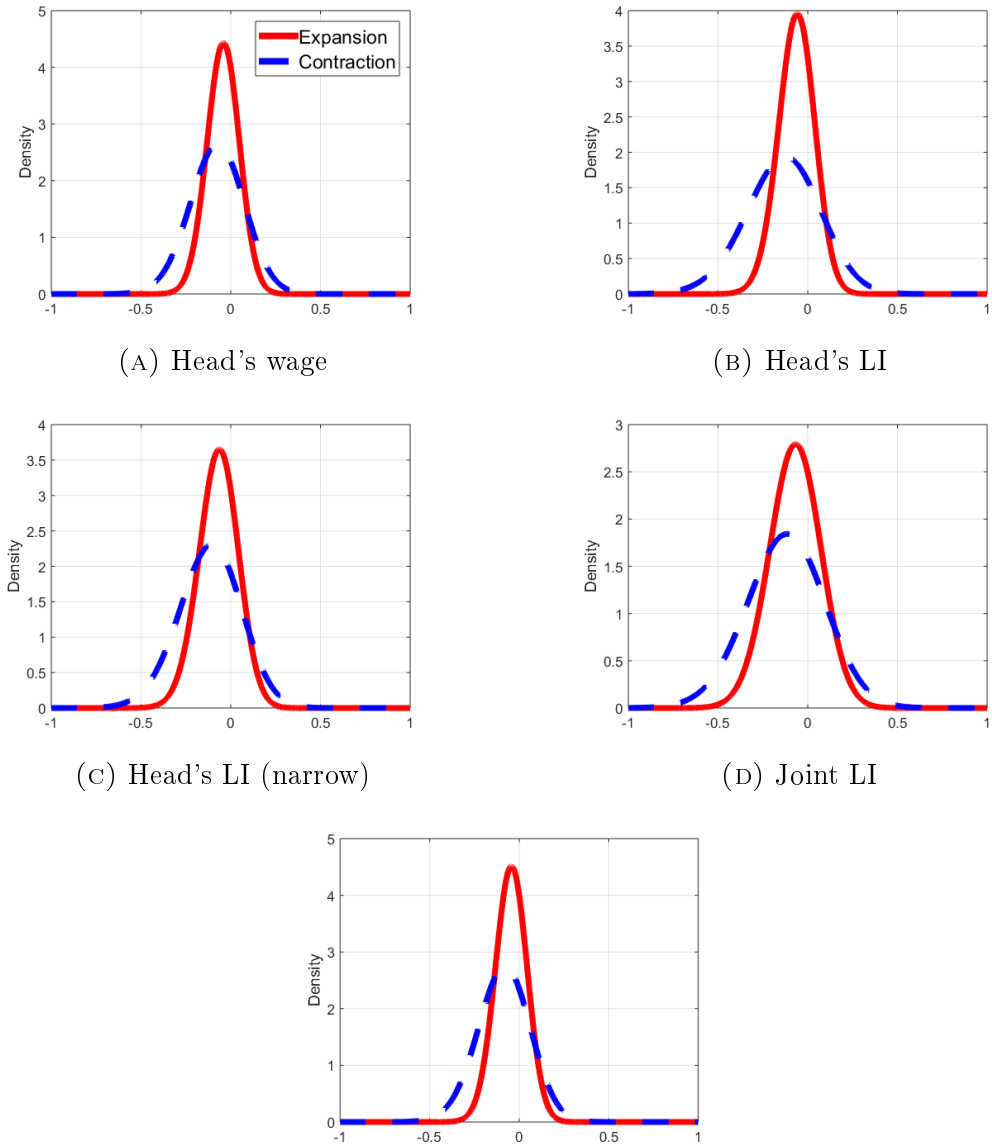
In this subsection, we quantify the importance of the cyclicality of labor income risk by computing how much the probability of a tail event (a 50% and a 100% increase/decrease in residual income) changes in recessions as compared with expansions for all 5 different income definitions. To this end, we first simulate a large number of individual (residual) income histories (N=100,000), assuming that their incomes follow Equation (2) with shocks distributed according to Equation (6). The number of simulated periods is 1000, where each period is either a contraction or an expansion. At the simulation step, we use the corresponding "expansionary" or "contractionary" parameters of income shocks depending on the contemporaneous aggregate state.

We end up having a large panel dataset $(100,000 \times 1000)$. At this stage, we have sufficient information to compute residual income changes, $u_{it} - u_{it-1}$, and assess the probabilities of tail events.[16] We sort all observations into one of 2 bins. The first bin contains all income changes that happened during "good" aggregate times, while the second one contains changes during bad times. We then plot the histograms of income changes in Figure 11. The blue area represents the histogram in contractions, while the red area represents the histogram in expansions.

Several observations are in order. First, and as expected, the distributions of income changes at recessionary times (in blue) have heavy tails. Second, the head's labor income (Panel (B)) exhibits the most pronounced difference between the red and blue distributions: the probability of large income drops (more than 100%) is the largest among the income types considered. Third, head's hourly wages, post-government joint labor income as well as narrowly-defined head's labor income seem to be changing the least among other income

[16] Technically, we obtain a distribution of (residual) income changes, from which we get the probabilities of tail events.

Figure 10: Estimated Distributions of Shocks, Expansions and Recessions



(a) Head's wage

(b) Head's LI

(c) Head's LI (narrow)

(d) Joint LI

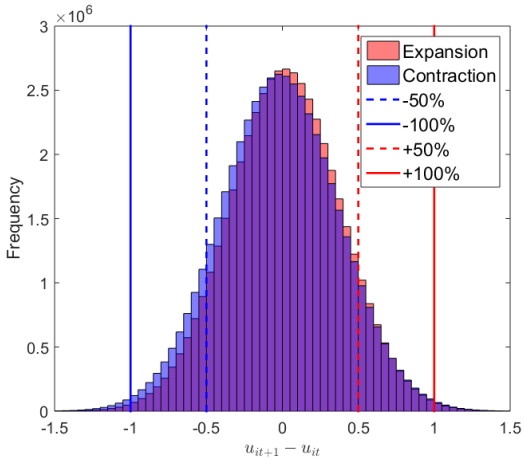
(e) Post-Govt Joint LI

Notes: Figure 10 plots the estimated distributions of residual income shocks (Equation (6)) for economic expansions (solid red) and contractions (dashed blue). The parameters of those distributions are taken from Table 6.

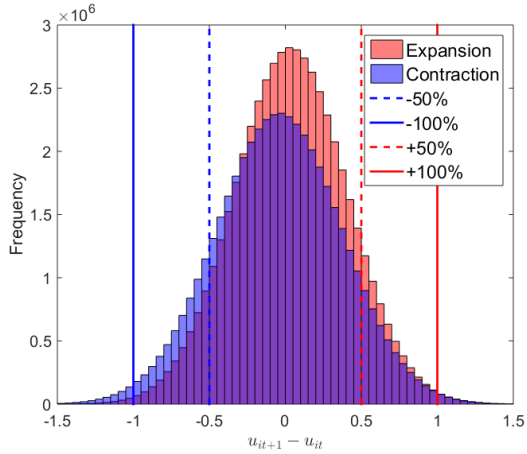
definitions, but their recessionary histograms still have heavier tails.

We next quantify the probabilities of tail events based on our simulation exercise and report the results in Table 8. Table 8 reports the probabilities that residual labor income increases or decreases by 50% or 100%, in expansions and recessions, for 5 different labor income definitions. There are two key takeaways. First, the probabilities of extreme tail events (a 100% increase/decrease) increase in contractions (the last column) compared with expansions (the second column) for all 5 income definitions. Moreover, the increase in more

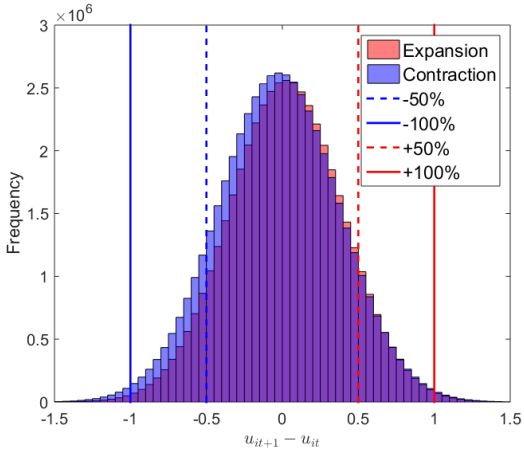
Figure 11: Simulated Distributions of (Residual) Income Changes



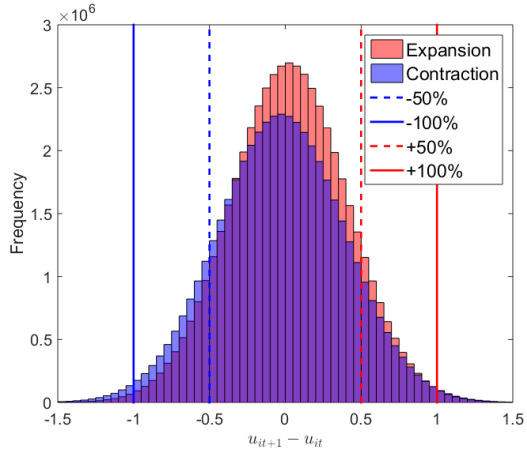
(A) Head's wage



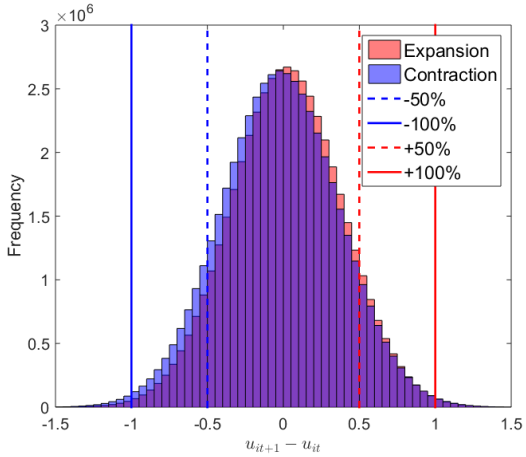
(B) Head's LI



(C) Head's LI (narrow)



(D) Joint LI



(E) Post-Govt Joint LI

Notes: Figure 11 plots the simulated distributions of (residual) income changes for all 5 income definitions considered in this paper. Histograms in red correspond to the case of economic expansions, while in blue — to contractions. See Section 6.2 for the simulation details.

Table 8: Estimated Probabilities of Tail Events, %

	Expansions		Contractions	
	$\leq -50\%$	$\leq -100\%$	$\leq -50\%$	$\leq -100\%$
Head Hourly Wage	7.9	0.3	10.6	0.6
Head LI	7.4	0.2	13.3	1.0
Head LI (narrow)	7.9	0.3	11.4	0.7
Joint (Head+Wife) LI	8.6	0.4	12.9	1.0
Post-Govt Joint LI	7.8	0.3	10.6	0.5
	$\geq +50\%$	$\geq +100\%$	$\geq +50\%$	$\geq +100\%$
Head Hourly Wage	9.4	0.4	9.0	0.4
Head LI	10.4	0.5	9.4	0.6
Head LI (narrow)	10.0	0.4	9.3	0.5
Joint (Head+Wife) LI	10.8	0.6	10.3	0.7
Post-Govt Joint LI	9.0	0.4	8.7	0.4

Notes: Table 8 is based on PSID Family Files over the period 1978-2014. The results are based on the simulation exercise described in Section 6.2. The top part of the table reports the estimated probabilities of income drops exceeding 50 and 100%, and the bottom part reports the estimated probabilities of income increases exceeding 50 and 100%. The left part of the table reports the corresponding probabilities for aggregate economic expansions, and the right part — for contractions.

pronounced for negative tail events (a 100% decrease). This is consistent with the observation that labor income risk is more dispersed in contractions than in expansions.

Second, when we compare the probabilities of tail events of different signs, large positive events (+50% and +100%, in the bottom panel) are more likely than large negative events (-50% and -100%, in the top panel) in expansions. In contractionary times, however, the pattern is reversed. The probabilities of large negative tail events (-50% and -100%) are higher than those for the large positive tail events (-50% and -100%). These facts reflect the procyclical nature of skewness of income shocks, which holds across all labor income definitions.

To better understand the implications of time-varying volatility and skewness, in Table 9 we report the changes in probabilities of tail events between contractions and expansions for each of 5 labor income definitions. The reported numbers are the ratios of the corresponding probabilities from Table 8. For example, number 35 in the first row reflects a 35% increase in the probability of having a 50% (residual) wage cut in recessions as compared with expansions.

Let us make three remarks. First, if we compare 5 labor income definitions, head's labor income shows the most pronounced movements in tail event probabilities between contractions and expansions. This is consistent with the implied cyclicality of labor income risk using our parameter estimates. Second, for all labor income definitions, the movement of negative tail events (the first two columns) is more pronounced than that of positive tail events (the last two columns). This is the procyclical skewness of labor income risk. Third, both second earners and government taxes and transfers contribute to mitigating the increasing odds of negative tail events in contractions. The increase in probability of a 50% (100%) residual income decline in recessions is suppressed by about 40% (60%) with

Table 9: Change In Tail Events Probabilities (Recessions vs. Expansions), %

Type of Income	-50%	-100%	$+50\%$	$+100\%$
Head Hourly Wage	35	100	-4	0
Head LI	80	400	-10	20
Head LI (narrow)	44	130	-7	25
Joint (Head+Wife) LI	50	150	-5	17
Post-Govt Joint LI	36	67	-3	0

Notes: Table 9 reports the change in probability (in %) of tail events in recessions as compared with expansions. The table is based on the estimated probabilities in Table 8.

the second earner and further lowered by about 30% (50%) through government taxes and transfers.

6.3 Evaluating the Magnitude of Income Shocks

While the previous discussion was set in terms of residual income, it is important to understand how large income shocks are relative to labor income itself. This subsection attempts to shed light on the quantitative relevance of income shocks.

In particular, we will be looking at the percentage change in labor income when an individual/household is hit by a large negative income shock. In order to avoid complicated simulations and to focus on showing the quantitative importance of income shocks, in this subsection we assume that both the persistent and transitory components of residual income (z_{it} and ε_{it}) are zero, and only an innovation to the persistent component η_{it} is allowed to change. Furthermore, to mimic a large negative income shock, we set $\eta_{it} = -3\sigma$, where σ is a standard deviation of the corresponding shock distribution (see Table 4).

Table 10 reports the results. For each income category (columns), it reports the percentage change in income following a large negative income shock that occurred in a recession (the first line) or in an expansion (the second line). In order to facilitate the comparison of different income categories, we focus on a prime-age male (40 years old) with a spouse, who is a college graduate and has no children. We obtain the labor income (not the labor income shock) corresponding to such a household by substituting estimates from Table 2 into Equation (1). Finally, expansionary/recessionary estimates of shock dispersion are taken from Table 4.

Table 10: Evaluating Magnitude of Income Shocks

	Wage	Head's LI	Head's LI (narrow)	Joint LI	Post-Govt LI
Recession	-36%	-45%	-36%	-49%	-34%
Expansion	-26%	-28%	-28%	-38%	-23%

Notes: Table 10 reports the percentage change in labor income following an extreme (3 standard deviations) negative labor income shock during aggregate expansion and recession. See text for more details.

Our results imply that the cyclicality of income shocks is quantitatively pronounced: a reduction in labor income following an extreme negative shock during aggregate expansion is

sizably weaker as compared with when the shock hits in a recession. In line with the earlier discussion, the starkest differences are found in the case of head's and joint labor incomes, while cyclical differences are weaker for hourly wages and post-government labor income.

7 Conclusion

In this paper, we analyze volatility and skewness of labor income risk over the business cycle. We systematically apply our analysis to 5 definitions of labor income, which allows us to disentangle the role of hourly wages, hours, second earners, government taxes and transfers, and labor market attachment. There are five main findings. First, for head's labor income, both variance and right skewness increase in contractions. Second, head's hourly wage is less cyclical than head's labor income in both variance and skewness, implying that changes in hours, possibly due to unemployment, are behind the cyclicality of head's labor income risk. Third, younger households exhibit stronger cyclicality of income volatility than older ones, although the level of volatility is lower. Fourth, we find that existence of a second earner lowers the level of skewness of income risk but not cyclicality. On the other hand, government taxes and transfers are found to lower both the level and the cyclicality of labor income volatility. But both channels help mitigate the increasing risk of negative tail events in recessions. Finally, among heads with strong labor market attachment, the cyclicality of labor income volatility becomes weaker, while the cyclicality of skewness remains. This implies that the choice whether to focus on heads with strong labor market attachment or not contributes partially to seemingly opposite conclusions about the cyclicality of labor income risk in the literature.

Let us conclude with listing four fruitful directions for future research. The first is to quantify the macroeconomic impact of countercyclical labor income risk, using a quantitative macro model. Another future direction is to identify macro shocks that could generate observed fluctuations in income risk. Third, more research on the intra-family insurance channel (through the second earner) would be useful. Finally, investigating what is going on with those with weak labor market attachment would help us better understand why the cyclicality of labor income risk is different depending on whether they are excluded.

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Table of Contents for Appendix

A Data

In this section, we first describe the way we construct variables from PSID data (Section A.1), and then we discuss the process of sample selection in full detail (Section A.2).

A.1 Variables

We break down the variables into 2 categories: demographic (Section A.1.1) and income-related (Section A.1.2) variables.

A.1.1 Demographic and Socioeconomic Variables

- **Head:** We identify current heads as those individuals within the family unit with a Sequence Number equal to 1. In PSID, the man is labeled as the household head and the woman as his spouse, conditional on this family being full (married couple). A woman can be considered to be the household's head only if she is not married. We select a new head in the case of split-off families.

- **Age:** Prior to 1996, PSID interviews were conducted annually (and since then, they are conducted biannually). However, the interview dates were not exactly a year apart, and, therefore, it can be the case that individuals report either the same age or numbers 2 years apart in consecutive waves. We create a consistent age variable by taking the age reported in the first year a particular individual appears in the survey and adding 1 to this variable in each subsequent year (2 for when the survey became biannual).

- **Education:** This paper is focused on people with the strongest labor market attachment (age 23-60); hence, it is natural to assume that individuals are typically done with their education by the time they are first interviewed. Our measure of education is equal to the number of complete years of college. This variable is, however, not reported consistently over years (sometimes, only bracketed information is available). We therefore reconstruct this variable by taking the maximum number reported for each individual over the years he/she was in the sample.

- **Family size:** We found that this variable is consistently reported throughout the waves.

A.1.2 Income Variables

- **Head's labor income:** This is among the most consistently reported income-related variables in PSID, available throughout all waves. However, this variable is bracketed - and, therefore, useless for our analysis - in waves 1968 and 1969. The PSID reporting standards are wave-specific: if, for example, head's labor income in waves 1970-1982 is bounded by $99,999, in the subsequent 10 waves (1983-1992) this variable is capped at $999,999. We make sure to drop all "capped" observations. Another issue associated with this variable is that starting from the 1994 wave, PSID stopped including the labor portions of farm and business income in head's labor income. We correct for this

by adding those income sources (the labor part of farm income and the labor part of business income) for wave 1994 and onward.

- **Wife's labor income:** We follow similar (to the previous variable) steps to construct this variable. The only difference is that PSID stopped including the labor portions of farm and business incomes for wives starting from wave 1993 (not 1994). We correct for that inconsistency similarly.

- **Joint labor income:** This variable is simply a sum of the head's and wife's labor incomes.

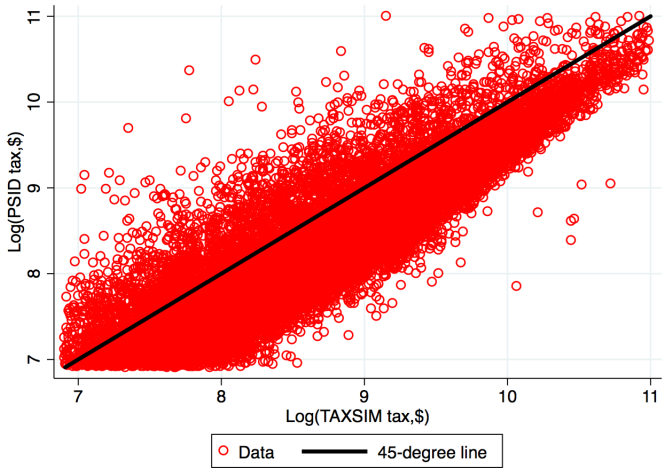
- **Post-government labor income:** We add family-wide transfers and subtract taxes from the spousal labor income to get the labor-related portion of the family-wide disposable income. Transfers and taxes are reported poorly in PSID; we discuss them next.

- **Transfers:** Transfer data is reported inconsistently across the years. In general, we consider the old-age, survivor, and disability insurance (routinely abbreviated as OASDI), unemployment insurance (coming from the household's head, spouse and from other family members (OFUMS)), food stamps, as well as some other minor categories (bonuses, miscellaneous transfers, transfers received by OFUMS).

- **Taxes:** Taxes are imputed by PSID analysts for waves 1978-1990. We want to use as many waves as possible, and so we need to construct a measure of household-wide taxes that will be consistent throughout the years. We use the TAXSIM system to impute the federal- and state-level liabilities for individuals in our sample[17]. In particular, we feed in the following information: the primary earner's (head's) labor income, the secondary earner's (spouse's) labor income, state that the household lives in (needed to compute state-level portion of the tax), the number of dependents (the family size minus 1 or 2 depending on the family composition), and the age of the primary earner. In order to check how consistent our measure of tax liabilities is with the tax data reported in PSID, we plot a scatter plot for these 2 measures pooled across years when both of them are available (1978-1990).

[17] TAXSIM is able to compute state taxes for 1978 and later; therefore, we drop years prior to 1978 in our final dataset.

Figure A.1: PSID Tax Against the TAXSIM Data, 1978-1990



Notes: Figure A.1 depicts a scatter plot of PSID tax data and the federal tax liabilities imputed through the TAXSIM. Every circle represents a particular family-year pair, covering the years 1978-1990. For a detailed description, see Section 2.

Figure A.1 shows that the data imputed through TAXSIM do a reasonable job, as the majority of observations lie on or close to the 45-degree line.

- **Head's labor income (narrow)** is obtained from the head's labor income data, when we drop observations which are below the minimum threshold. The threshold is defined as half of the current minimum hourly wage multiplied by 520 hours (13 weeks, 40 hours in each). The data on the minimum hourly wage comes from FRED[18].

A.2 Sample Selection

Our baseline sample comes from PSID Family Files for the period 1969-2014. We use Individual Files to track individuals over time and subsequently use information from the Family Files to obtain family-wide variables. We track only heads of households; therefore, any "split-off" family we treat as a new family. In what follows, we provide a step-by-step algorithm of data preparation. Table A.1 summarizes the verbal description.

1. We start off with downloading the 1968-2014 PSID files;
2. families that are part of SEO along with the Latino subsample are dropped;
3. only households' heads are tracked;
4. observations with missing or non-positive head labor incomes are dropped;
5. observations with negative spousal labor incomes are dropped;
6. years prior to 1978 are dropped;

[18] https://fred.stlouisfed.org

7. heads aged between 23 to 60 are considered;
8. the top 1% with respect to head's and wife's labor incomes are trimmed;
9. households with income growth anomalies (annual log growth rate must be between $\frac{1}{20}$ and 20) are dropped.

Figure A.2 illustrates the number of families in the final sample across years.

Figure A.2: Number of Families in the Final Sample

Notes: Figure A.2 is based on Family Files from PSID over the period 1978-2014. Each dot indicates the number of families in a given year, after selection criteria outlined in Appendix A.2 have been applied.

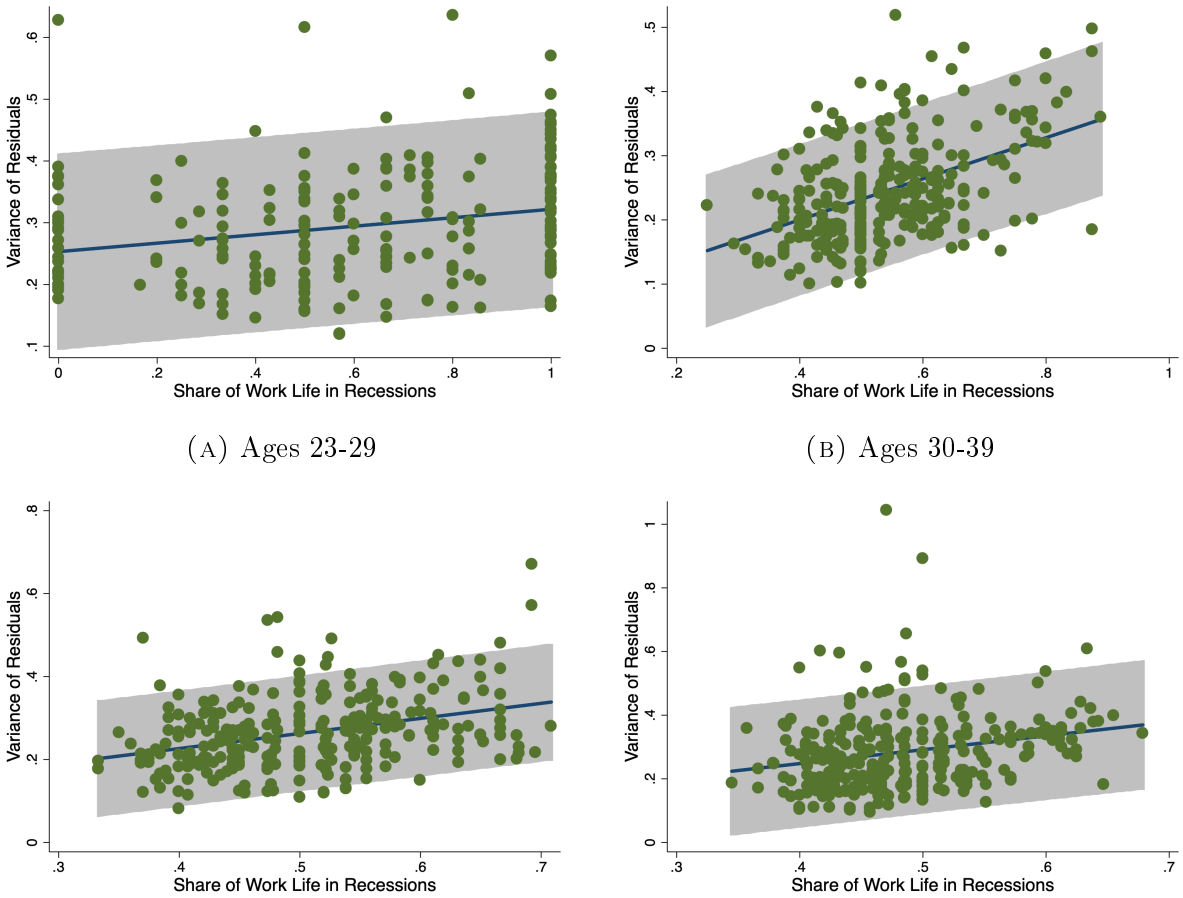
Table A.1: Number of Observations Kept At Each Step

Step	Observations
Start	3,011,697
Only heads	278,119
No SEO, Latino	153,037
Years $\geq$1978	97,400
No missing, negative head's LI	86,477
Ages 23-60	71,425
No outliers	62,903
No growth anomalies	54,744

Notes: Table A.1 reports the total number of remaining observations after each step of data preparation (see Appendix A.2).

A.3 Variance of Residuals as a Function of Work History

Figure A.3: Variance of Residuals as a Function of Work History



(a) Ages 23-29

(b) Ages 30-39

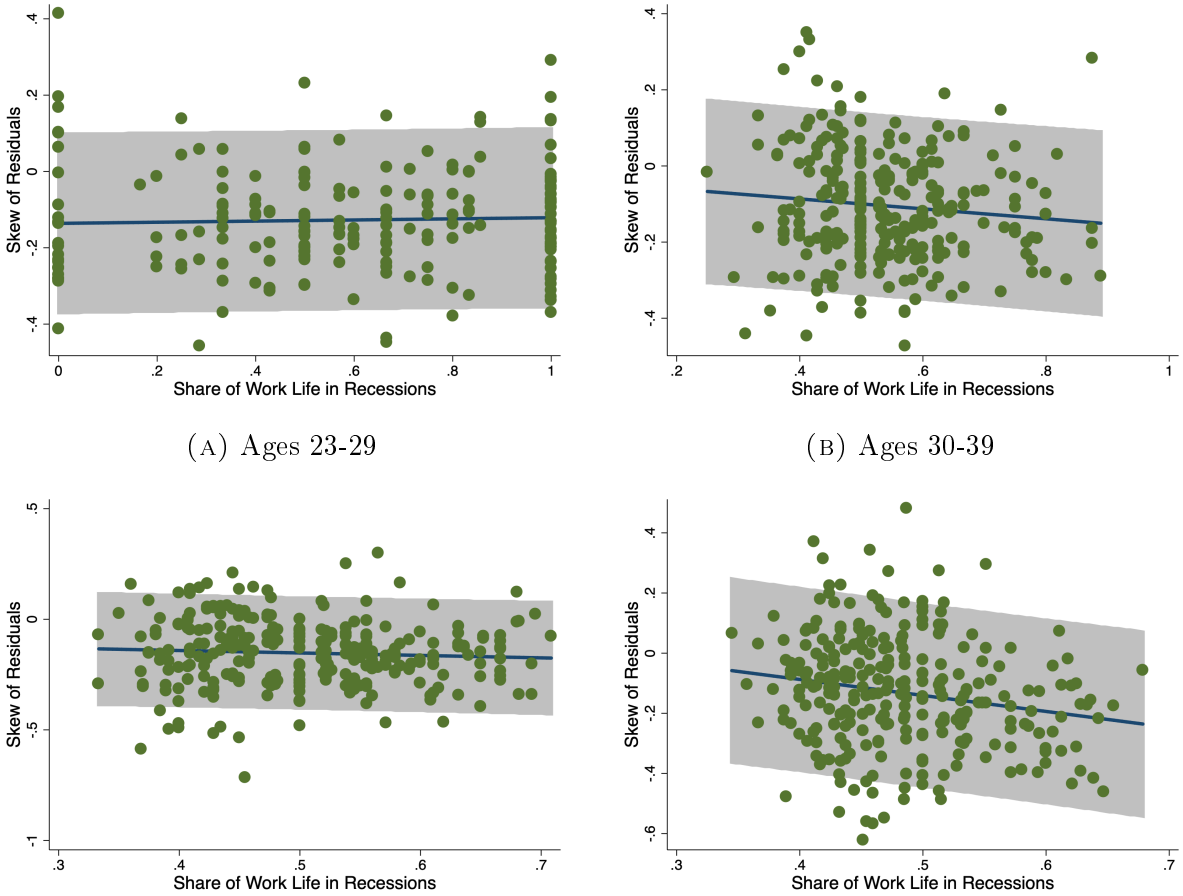
(c) Ages 40-49

(d) Ages 50-60

Notes: Figure A.3 plots the variance of residuals from the estimation of Equation (1) for 4 age groups: 23-29, 30-39, 40-49, and 50-60 years old. Each green dot represents a cross-sectional variance of $\hat{u}$ computed over a particular (age,year) cell. Grey bands indicate 90% confidence bounds. The share of work history is a continuous variable bounded between 0 and 1. It represents a share of (working) life each cohort spent in recession.

A.4 Skew of Residuals as a Function of Work History

Figure A.4: Skew of Residuals as a Function of Work History



(a) Ages 23-29

(b) Ages 30-39

(c) Ages 40-49

(d) Ages 50-60

Notes: Figure A.4 plots the variance of residuals from the estimation of Equation (1) for 4 age groups: 23-29, 30-39, 40-49, and 50-60 years old. Each green dot represents a cross-sectional coefficient of skewness of $\hat{u}$ computed over a particular (age, year) cell. Grey bands indicate 90% confidence bounds. The share of work history is a continuous variable bounded between 0 and 1. It represents a share of (working) life each cohort spent in recession.

A.5 Recessionary and Expansionary Years: A Comparison

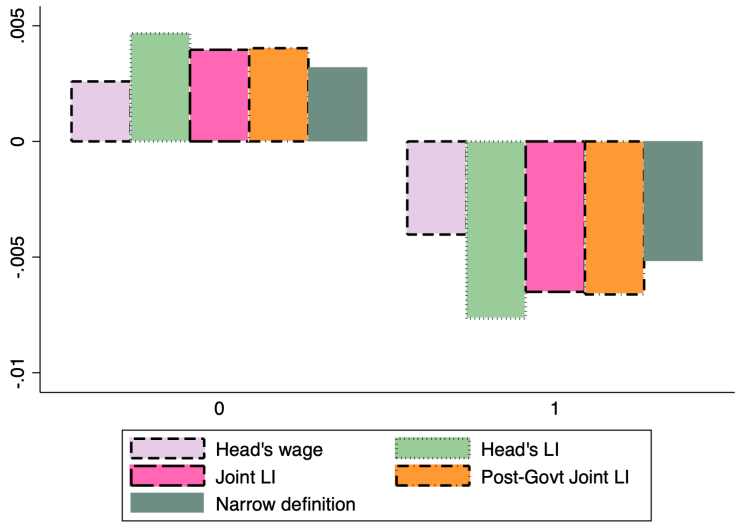
Year	NBER	GDP	GNP per capita
1978			
1979		✓	✓
1980		✓	✓
1981	✓	✓	✓
1982	✓	✓	✓
1983			
1984			
1985			
1986			
1987			✓
1988			
1989		✓	✓
1990		✓	✓
1991	✓	✓	✓
1992		✓	✓
1993			✓
1994			
1995		✓	✓
1996		✓	✓
1997			
1998			
1999			
2000			
2001	✓	✓	✓
2002		✓	✓
2003		✓	✓
2004			
2005			
2006			
2007		✓	✓
2008	✓	✓	✓
2009	✓	✓	✓
2010		✓	✓
2011			✓
2012			✓
2013			✓
2014			

Notes: The table reports the classification of sample years (1978-2014) into recessions and expansions. Recessionary years are marked with a checkmark. The table provides 3 classification: based on real GDP, real GNP per capita, and NBER recessionary years.

B Alternative Measures of Business Cycle

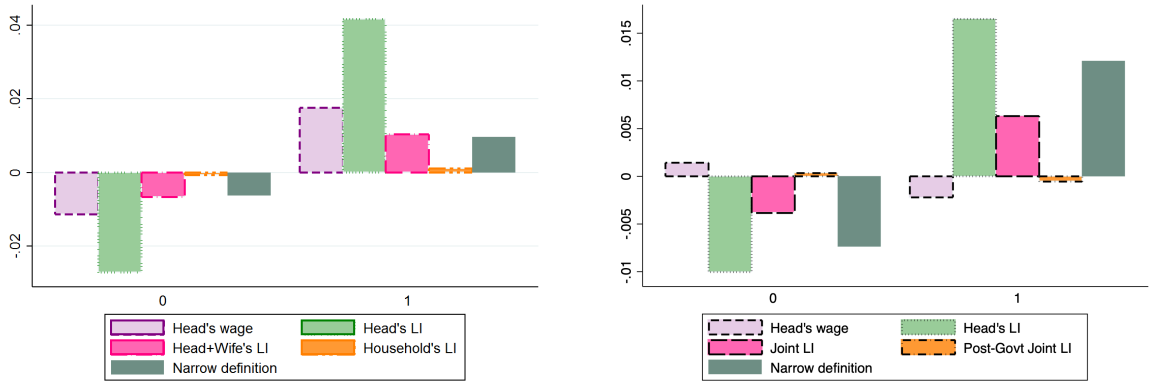
B.1 NBER Recession Dates

Figure A.5: Volatility of Idiosyncratic Earnings Risk by NBER Recession Dates



Notes: Figure A.5 is based on Family Files from PSID over the period 1978-2014. Each year from the period 1978-2014 is coded as either 0 (NBER recession), or 1 (otherwise). The standard deviations shown are averages over years in the bin. Each bin contains standard deviations for 5 measures of labor income: head's wage, head's labor income, joint labor income, post-government joint labor labor income, and head's labor income (narrow definition).

Figure A.6: Skewness of Idiosyncratic Earnings Risk, by NBER Recession Dates

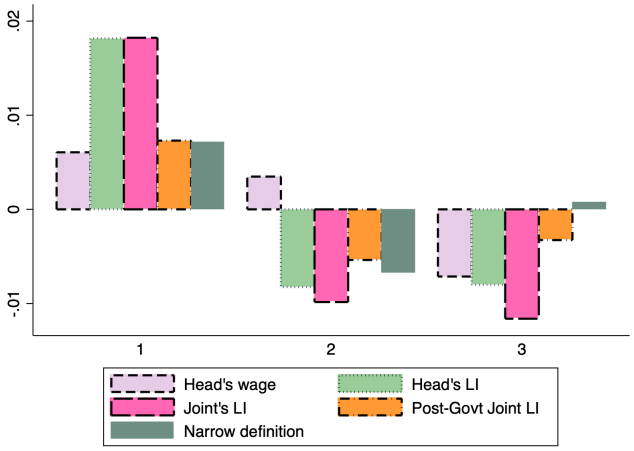


(A) Third central moment (B) Kelly's measure

Notes: Figure A.6 is based on PSID Family Files over the period 1978-2014. Panel A plots the third central moment, Panel B plots the Kelly's measure. Each year from the period 1978-2014 is coded as either 0 (NBER recession), or 1 (otherwise). The measures of skewness shown are averages over years in the bin. Each bin contains skewness measures for 5 different types of labor income: head's wage, head's labor income, joint labor income, post-government joint labor labor income and head's labor income (narrow definition).

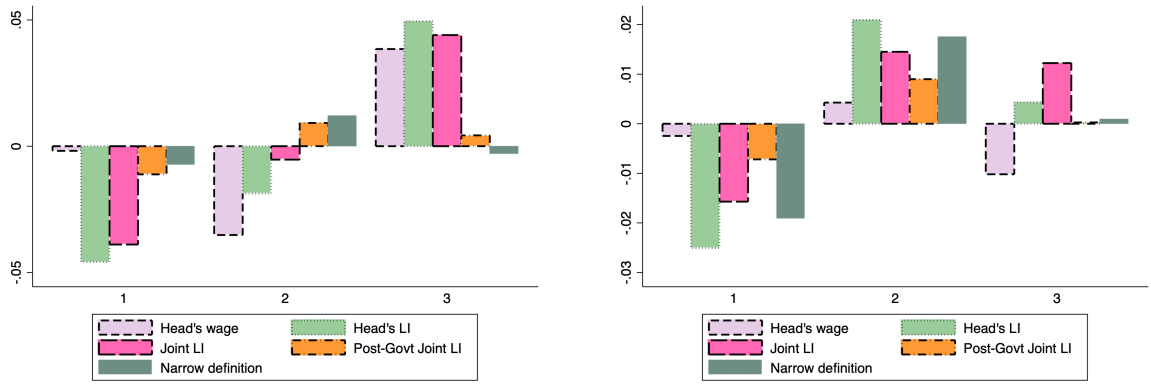
B.2 Mean Income

Figure A.7: Volatility of Idiosyncratic Earnings Risk by Mean Income Growth Tertile



Notes: Figure A.7 is based on Family Files from PSID over the period 1978-2014. Each year from the period 1978-2014 is classified in one of 3 bins, depending on which tertile the growth rate of mean income in that year falls into. Tertile 1 contains years with the lowest growth rate of mean income, while tertile 3 contains years with the highest growth rates. The standard deviations shown are averages over years in the bin. Each tertile contains standard deviations for 5 measures of labor income: head's wage, head's labor income, joint labor income, post-government joint labor labor income, and head's labor income (narrowly defined).

Figure A.8: Skewness of Idiosyncratic Earnings Risk, By Mean Income Growth Tertile



(A) Third central moment (B) Kelly's measure

Notes: Figure A.8 is based on PSID Family Files over the period 1978-2014. Panel A plots the third central moment, and Panel B plots the Kelly's measure. Each year from the period 1978-2014 is classified in one out of 3 bins, depending on which tertile the growth rate of mean income in that year falls into. Tertile 1 contains years with the lowest growth rate of mean income, while tertile 3 contains years with the highest growth rates. The measures of skewness shown are averages over years in the bin. Each tertile contains skewness measures for 5 different types of labor income: head's wage, head's labor income, joint labor income, post-government joint labor income and head's labor income (narrow definition).