Lifecycle Earnings Risk and Insurance: New Evidence from Australia*

Darapheak Tin†
Australian National University

Chung Tran‡
Australian National University

October 2022

Abstract

This paper studies the nature of earnings dynamics in Australia, using the Household, Income and Labour Dynamics in Australia (HILDA) Survey 2001-2020. Our findings indicate that the distribution of earnings shocks displays negative skewness and excess kurtosis, deviating from the conventional linearity and normality assumptions. There is variation in the sources of earning shocks. Wage changes are strongly associated with earnings changes and account more for the dispersion of earnings shocks; meanwhile, the contribution of hour changes is largely absent in upward movement and relatively small in downward movement of earnings changes. Furthermore, family and government insurance play distinct roles in reducing exposure to earnings risk. Government insurance embedded in the targeted transfer system is more important in mitigating the dispersion of earnings shocks, whereas family insurance via income pooling and adjustment of secondary earners' labour market activities is dominant in reducing the magnitude and likelihood of extreme and rare shocks. Finally, the magnitude and persistence of earnings risk as well as the insurance role of family and government vary significantly across primary earner's gender, marital and parental status.

JEL: E24, H24, H31, J31.

Keywords: Income dynamics; Earnings risk; Higher-order moments; Non-Gaussian shocks; Family insurance; Government insurance; Inequality.

*We would lile to thank the editor and referees for their constructive comments. We also appreciate comments from Robert Breunig, Timothy Kam, Timo Henckel and the participants of A-LIFE Conference, WAMS 2021, and Seminars at Australian Treasury and Australian National University. This research is supported by an Australian Research Council Grant (DP210102784).

†Research School of Economics, Australian National University, email: darapheak.tin@anu.edu.au

‡Research School of Economics, Australian National University, email: chung.tran@anu.edu.au

1 Introduction

Understanding the nature of earnings risk is crucial for better understanding of income dynamics, trends in income equality as well as the insurance role of a redistributive tax and transfer system. There is a growing literature that takes advantage of administrative and household datasets, and new statistical techniques to explore the rich dynamics of income process. Recent developments, including Arellano, Blundell and Bonhomme (2017), De Nardi et al. (2021), Guvenen et al. (2021) and Halvorsen et al. (2020), have identified non-Gaussian and non-linearity features of residual income fluctuations. These studies demonstrate that the persistence of innovations is not uniform but exhibits systematic asymmetries, and that the distribution of innovations to income displays strong negative (left) skewness and excess (leptokurtic) kurtosis than normally distributed shocks. De Nardi et al. (2021) and Halvorsen et al. (2020) also examine on the role of family and government in insuring against earnings risk. A key result from these studies is that family and government are important sources of insurance. De Nardi et al. (2021) in particular finds that family insurance in the US is larger than that in the Netherlands.

In a similar vein, our paper is the first to comprehensively examine the distribution of earnings risk and the degree of insurance provided by family and government in Australia. We use micro data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey release 20 (2001-2020). Similar to Guvenen et al. (2021) and De Nardi et al. (2021), we adopt nonparametric methods. Our results reveal that the features of income dynamics documented previously for other countries are observed in Australia; however, there are differences in the sources of earnings risks and the insurance roles of family and government.

More specifically, we begin by calculating second- and higher-order moments of residual labour earnings shocks for primary earners (heads of households) in the 25-64 age range and are employees in non-own businesses.[1] We uncover a rich shock process that exhibits strong non-linear and non-Gaussian features across age and income history (grouped by decile of past income).[2] Specifically, the variance of earnings shocks (*second-order risk*) is most pronounced at the lower income deciles, especially for older cohorts. Those in the upper deciles experience a relatively high dispersion, albeit several times lower than that of the former group. Moreover, excluding the poorest, the shock distribution is negatively skewed (*third-order risk*) and leptokurtic (*fourth-order risk*). Indeed, there are significant differences in the degrees of variance, skewness and kurtosis by age cohort and income history. In our extension, we estimate a parametric model of earnings dynamics with non-linearity and non-normality assumptions. We find that our estimated model is capable of reproducing the overall pattern of these key empirical facts.

Focusing on the dynamics of labour earnings allows us to disentangle the moments of earnings changes into those of wage and work hour changes. Our findings broadly indicate that wage changes mainly account for the dispersion of earnings changes. Meanwhile, changes in hours induce the negative skewness and the excess kurtosis. Restricting the sample to workers with consistent employment history (to partially remove short-term hour irregularities) or by demographic attributes does not alter this conclusion. In addition, we observe the following asymmetry. Barring those in the bottom decile, the role of hours is negligible on the positive changes in earnings and contributes by a relatively

[1] The terms *shocks* and *changes* are used interchangeably to refer to residual shocks net of age and time effects.

[2] Income history of an individual is defined as the income decile to which he/she belonged in the previous period, and may be referred to as the past/previous income decile.

lesser degree to the negative earnings changes. In contrast, earnings changes in both directions are associated strongly with wage movement.

We next examine the extent to which earnings risk is mitigated by implicit and explicit forms of insurance arrangement. For this purpose, instead of labour earnings, we use the regular market earnings which is a broader income definition comprising earnings from all market sources. We find two dominant channels of (external) insurance: *within family responses,* i.e. family market income insurance, and *net public transfers,* i.e. government transfer insurance. To quantify insurance, we compare distributional properties of income changes at various levels. Technically, the differences between moment statistics of the distributions of individual regular market income changes and family pre-government income changes capture insurance components pertaining to family market earnings and private transfers. Analogously, the differences between those of family pre- and post-government income changes imply the role of government insurance provided via the tax and transfer system.[3]

In our analysis, insurance has two primary roles: (i) as a mitigator of the variation of shocks (or *the second-order risk*), and (ii) as a mitigator of the magnitude and probability of shocks at the extreme which correspond to skewness and kurtosis of income shock distributions (*the third- and fourth-order risks*), respectively. In terms of insurance against the second-order risk, family insurance is small and limited to primary earners in the bottom decile of past income, whereas government transfer insurance is larger and more robust across a wide range of specifications. Against the third- and fourth-order risks, on the other hand, family market income insurance plays a more dominant role. Overall, family market income and government transfer are vital sources of insurance against earnings risks, but they are not capable of providing full insurance to completely eliminate the non-Gaussian and non-linear elements from the household disposable income dynamics.

As an extension, we further investigate how earnings risks for different age and income groups are affected by demographic factors. We mainly focus on three attributes: *gender*, *marital* and *parental status* that are prominently embedded in the Australian welfare system. The results suggest that the shock distributions still display negative skewness and excess kurtosis even after taking into account these idiosyncrasies. However, there are pronounced disproportionate effects of government insurance by household type, partly a result of the differences in income dynamics by demographics and the targeted nature of the Australian welfare system. For instance, lower-income female heads of households and non-parents both confront persistently high income risks, but due to the targetedness of transfer programs, the former group benefits significantly more from government insurance. Consequently, the gap in disposable income risks between female and male primary earners shrinks substantially, whereas that between parents and non-parents remains wide. Conversely, family insurance appears to be more important for those not targeted by the means-tested public transfer schemes, including non-parents and upper income partnered parents. Together with our finding of weak spousal and strong public responses to individual earnings shocks, this implies the provision of government insurance potentially crowds out family insurance, which is consistent with a conjecture by De Nardi et al. (2021) based on their comparison of the US and the Netherlands.

Related literature. Our paper contributes to a growing literature that studies non-Gaussian and non-linear features of earnings dynamics (e.g., De Nardi et al. 2021; Guvenen et al. 2021 and Halvorsen et al. 2020). We provide a new case study using Australian microdata. Unlike prior studies

[3] Throughout the discussion, post-government income may also be referred to as after-tax-and-transfer income, post-fiscal, or disposable income.

revolving around male workers, ours focuses on primary earners to account for the sizeable proportion (39%) of female headed households in our sample.[4] The results point at a strong resemblance between Australia and other OECD countries previously examined in the literature - in particular the US (Guvenen et al. 2021), the Netherlands (De Nardi et al. 2021) and Norway (Halvorsen et al. 2020). Notwithstanding, there are some notable differences. For instance, as opposed to the US and the Netherlands where wage and hour changes contribute in almost equal proportion to the second-order earnings risk, the principal driver in Australia appears to be wage changes. Another difference is that the roles of family and government insurance in Australia generally do not overlap. Government insurance smooths out small and moderate shocks while family insurance tends to respond to more extreme events.

This paper is also related to the body of work studying the role of government insurance in heterogeneous agent models accounting for family structure (e.g., De Nardi, Fella and Paz-Pardo 2020; Kaygusuz 2015 and Nishiyama 2019). Kaygusuz (2015) and Nishiyama (2019) assume normally distributed earnings shocks and find that the US's spousal and survival benefits transfer welfare from two-earner to single-earner households. De Nardi, Fella and Paz-Pardo (2020) show the extent to which the government helps households depends on the risk distribution that they face and their family composition. Similarly, our results suggest that those facing more persistence risks such as female headed households (half of whom belong to dual-earner households) benefit greatly from government insurance against earnings risk. Therefore, relaxing the Gaussian and linear assumptions to account for more realistic risk structure may have considerable influence on quantitative results.

Furthermore, our work contributes directly to the understanding of income dynamics and inequality in Australia. The early literature (e.g., Chatterjee, Singh and Stone 2016; Kaplan, Cava and Stone 2018 and Freestone 2018) show an increase in inequality in labour earnings is mainly due to residual factors reflecting idiosyncratic wage risks drawn from normal distributions. These studies commonly assume that income shocks follow a Gaussian process and estimate a linear model of risk. Overall, our findings agree with the previous work that residual wage shocks drive the residual earnings fluctuations. In addition, we further illustrate that the shock process is more complex and deviates from the normality and symmetry assumptions, and that hours also have a role to play in shaping the extreme ends of the earnings shock distribution. Finally, our paper is connected to the body of empirical studies on the redistributive effects of the Australian tax and transfer policies (e.g., Herault and Azpitarte 2015 and Tran and Zakariyya 2021). These studies mainly focus on the first-order moment of income level. Differently, this paper emphasizes the second- and higher-order moments of income changes. In doing so, we uncover the drivers of risks, and the functions and limitations of family and government insurance, which are fundamental for understanding the dynamics of income inequality as well as the insurance role of the Australian tax and transfer system.

The paper hereinafter proceeds as follows. Section 2 provides a description of the dataset, descriptive statistics and methodology. Section 3 discusses the main results. Section 4 presents extensions. Section 5 concludes. Appendices report additional information and results.

[4] We show separate results for male primary earners in section 4 and in the appendix F.1 from Figure F.2 to Figure F.8. We find no significant qualitative difference. That is, our conclusion based on the male primary earner sample would be similar to the combined sample used in the main study.

2 Data and methodology

2.1 Data and variable construction

We use data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey Restricted Release 20 (2001 – 2020). Began in 2001 and has since been conducted on an annual basis, HILDA is a nationally representative panel data of Australian households on a wide range of subjects pertaining to family and labour market dynamics. The survey collects information on respondents and their family members, including demographics, earnings and their sources, taxes and transfers, household and family identifiers, and a rich set of covariates that enables a more comprehensive study. Compared to the General Release dataset, the Restricted Release also contains details on variables such as income and wealth (not confidentialised via top coding), employment characteristics and birth dates. This allows for more accurate estimations of total individual and household incomes, and taxes and transfers.[5]

Note that, we include wave 20, which corresponds to the 2019-20 financial year (from 01 July 2019 to 30 June 2020), as a larger sample size enhances the quality of our moment statistics. This means income, tax, and benefit variables are affected to an extent by the COVID-19 pandemic. Nonetheless, our sensitivity tests shows that the findings are robust to the inclusion of wave 20. This could be due to two reasons. First, we control for time effect. Second, the 2019-20 data includes at most 3 months of the pandemic effect.

Our core unit of measurement when documenting earnings risk is an adult individual who legally pays taxes in Australia. Restricting the sample to only employees (of non-own businesses), we retain 152, 903 observations. The choice to exclude employers and employees of family-own businesses (paid or unpaid) is made for two reasons. First, the group constitutes a small proportion of the sample (26,771 observations). The methodology employed (e.g., to get 3-year average residual differences) and the sample selection criteria (e.g., consistent employment history) further reduce the sample size. This matters when one wishes to obtain reliable moment statistics conditioning on subgroups (age, income history and demographics). Second, our objective is to produce comparable results with the previous work on other OECD countries. For similar reasons, youth (15-24) and elderly employees (65+) are not considered in this study. We turn to family as the main unit of analysis when analysing the insurance role of family and government. The primary sample here involves single and partnered (married or in de facto relationship) primary earners distinguished by their unique family unit identifiers. For our purpose, the terms "family" and "household" are interchangeable. A family unit usually includes spouses, independent children and other members of the same family unit. Note that, a household unit defined in the HILDA data may include multiple family units. As an example, the survey records independent lone persons in a shared household as separate family units living within the same household unit.

At the weekly level, the HILDA survey reports usual weekly earnings and usual work hours of the financial year immediately preceding the interview. Our measures of weekly wage rates are derived from these two figures. A caveat is that these variables do not capture interim unemployment spells and other short-term hour irregularities. The estimates of weekly earnings and its constituents are

[5] Compared to the household survey data, the merit of using administrative data is the significantly larger and thus more representative sample of the Australian population. However, at the time of writing, we are not aware of any Australian administrative datasets that contain information on work hours and demographic structure which are essential for our decomposition exercise of the earnings dynamics.

thus subject to measurement errors that likely result in an underestimation of the role of hours in driving the dynamics of earnings.[6] As a partial remedy in subsection 3.1, we restrict the sample to employees with consistent workforce participation history - defined as those having worked one day or more per week for at least 18 years of observation and received at least the minimum hourly wage of A$20 (in 2018 dollar). We relax this requirement, by setting the cutoff work duration to 10 years, for certain subgroups (e.g., non-parents) to allow sufficient sample size. Regardless, because of the large differences found in our study between the roles of wages and hours in explaining transitory and persistent earnings changes, we believe the true patterns are unlikely to deviate in any significant manner from our estimates.

For our analysis on family and government insurance effects in subsection 3.2, on the other hand, we include all employees regardless of their work history. The reason is major welfare programs in Australia such as the Family Tax Benefit (FTB part A and part B) and JobSeeker Payment are not conditional on labour market participation. Thus, comprehending the full impact of government insurance demands that we do not drop those who temporarily exited the workforce. Moreover, the measurement error problem is of less concern to our annual estimates. Simply multiplying the usual weekly earnings by work weeks to obtain the annual figures would indeed introduce significant measurement errors and lead to clustering of hours as a consequence of omitting information on short-term changes during the year. HILDA eases this constraint by collecting annual income, tax and transfer data on a completed financial year preceding the date of interview, which permits more accuracy in imputing tax, transfer, and disposable income at the annual level. Of particular relevance to the study of insurance is that estimates of family income encompass all individual members' regular market income flows from market sources such as wage and salary, business income, investment income and regular private pension. While labour income is useful for our decomposition exercise, it fails to provide a complete picture of insurance against risk. Hence, the broader market income definition is used. Jointly with private transfer, this makes up family pre-government income.

Since annual data captures more within-year variation, the annual income variables are examined separately from the weekly variables. Besides, because tax and benefit are estimated and reported annually in the survey, it is through the annual variables that the government insurance effects are estimated.[7] More precisely, the schema is as follows:

Weekly income variables:

$$\begin{cases} \text{Hourly wage} \xrightarrow[\text{(via work hours)}]{\text{self-insurance}} \text{Total weekly earnings} \\ \text{Total weekly earnings} \xrightarrow[\text{(via members' earnings)}]{\text{family market income insurance}} \text{Total weekly family earnings} \end{cases}$$

Annual income variables:

[6] De Nardi et al. (2021) reports an overestimation of the role of wages in driving the earnings dynamics by comparing their estimates based on household surveys to those using administrative datasets, but the margins of errors are small and the qualitative patterns are maintained.

[7] We work with annual data and thus lack information on benefits or components of benefits that accrue at a higher frequency (e.g., fortnightly).

$$\begin{cases} \text{Regular market income} \xrightarrow[\text{(via members' annual earnings)}]{\text{family market income insurance}} \text{Family regular market income} \\ \text{Family regular market income} \xrightarrow[\text{(via private and irregular transfers)}]{\text{family transfer insurance}} \text{Family pre-gov't income} \\ \text{Family pre-gov't income} \xrightarrow[\text{(via combined income taxes)}]{\text{government tax insurance}} \text{Family post-tax private income} \\ \text{Family post-tax private income} \xrightarrow[\text{(via public transfers)}]{\text{government transfer insurance}} \text{Family post-gov't income} \end{cases}$$

ndividual and family units play different but equally important roles throughout the analysis. Individual unit is pivotal for computing tax statistics due to the separate tax filing system in Australia. Family unit, on the other hand, is the primary basis for computing transfer statistics because an eligibility criterion for major transfer programs is means testing combined family income as opposed to individual income. Particularly, variables at the family level must be calculated and handled explicitly apart from those at the individual level. This is done by modifying the HILDA tax-benefit model to first decouple the benefit system from the tax system and calculate individual taxable and adjusted taxable income. Afterwards, individual values are merged back together by family identifier to construct various family income definitions (e.g., gross adjusted taxable family income) which are then used to calculate social benefits and their related supplements. Public transfers are assumed (as done in the HILDA survey) to be shared evenly among members of the same family, except for maternity support which is assigned only to mothers. In this manner, the approach allows us to bypass the need for parametric functions in deriving relevant tax-benefit variables and calculating moments of pre- and post-government income variables.

Table 1 presents descriptive statistics of some of the main variables at individual and family levels in 2020.

Primary Earner		N	Mean	Median	SD	Min	Max
Age	Individual	5,064	41.62	40	11.42	25	64
	Family	5,064	-	-	-	-	-
Weekly hours	Individual	5,064	38.39	40	12.17	0	137
	Family	5,064	53.17	48	30.83	0	227
Weekly wage	Individual	5,064	1,602.68	1,407.68	994.18	0.00	13,106.03
	Family	5,064	2,366.64	2,135.80	1,479.03	0.00	15,752.48
Labour Income	Individual	5,064	85,855.68	75,723.73	56,891.76	0.00	970,817.13
	Family	5,064	129,099.10	114,556.42	85,839.93	0.00	1.13e+06
Market income	Individual	5,064	88,836.96	77,665.37	60,488.81	-42,502.38	970,817.13
	Family	5,064	139,555.66	121,949.19	102,986.36	-42,016.96	2.74e+06
Private transfer	Individual	5,064	446.73	0.00	3,197.68	0.00	132,911.66
	Family	5,064	809.84	0.00	5,273.85	0.00	168,922.17
Total income tax	Individual	5,064	20,926.39	15,641.81	23,154.97	-2,259.09	413,873.91
	Family	5,064	31,058.35	23,178.26	37,202.65	-7,960.70	1.16e+06
Public transfer	Individual	5,064	2,133.53	0.00	5,764.68	0.00	72,231.70
	Family	5,064	5,205.20	0.00	10,679.92	0.00	97,191.41

Table 1: **Summary statistics of primary earners in financial year 2020**. The values of income, tax liabilities and transfers are expressed in 2018 AUD.

2.2 Methodology

We employ a nonparametric approach from Guvenen et al. (2021) to characterize earnings dynamics, and similar metrics as in De Nardi et al. (2021) to measure family and government insurance. Accordingly, the terms "*insurance*" is defined as the extent to which the second- and higher-order risks (*standard deviation*, *skewness* and *kurtosis* of an income shock distribution) are mitigated by a particular income component. The current practice involves comparisons of moment properties between distributions of shocks at different income layers in a successive fashion, ranging from individual market earnings to household disposable income, to capture each component's contribution (i.e., insurance) to the eventual risk outcome.

Income growth rate. As in Guvenen et al. (2021), the income process abstracts from macroeconomic events, time trends and deterministic life cycle factors. More precisely, we first purge age and time effects from income variables by taking a least squares regression of log income on quadratic age terms and dummy year variables

$$\log y_{i,t} = \beta_1 age_{i,t} + \beta_2 age_{i,t}^2 + \beta_3 year_t + \mu_{i,t}, \tag{1}$$

where $y_{i,t}$ is income of individual i at time t. Next, we compute theresidual income ($\widehat{\mu}_{i,t}$) from equation 1 for each individual i in year t and calculate the changes between two years.[8] The resulting n-period residual income changes are given by $\Delta^n_{\widehat{\mu}_{i,t}} = \widehat{\mu}_{i,t} - \widehat{\mu}_{i,t-n}$. Technically, $\Delta^n_{\widehat{\mu}_{i,t}}$ represents a change in income of person i at time t occurring in n periods after controlling for the age and time effects. For example, when $n = 1$, $\Delta^1_{\widehat{\mu}_{i,t}}$ is the annual growth rate of residual income. We refer to these changes in 'residual' income as *income shock*s.

Figure 1 reports an empirical distribution of the annual residual income shocks. The second, third, and fourth moments of the distribution are named *second-*, *third-*, and *fourth-order earnings risk*, respectively. In this analysis, we examine both annual ($n = 1$) and 3-year ($n = 3$) average residual changes. Without knowledge of the nature of measurement errors in the survey data, the former contains both transitory shocks and measurement errors. Therefore, by partially removing the transitory component, the latter's statistics achieve two objectives. First, they capture the more persistent element of shocks. Second, they help reduce the influence of measurement errors.

Group-specific income shocks. Individual income shocks are subsequently grouped by (i) *age cohort* and (ii) *income history*. There are four age cohorts, namely $\{25-34,\ 35-44,\ 45-54,\ 55-64\}$. Income history, measured by either past usual weekly earnings or past regular annual market income, is grouped by decile.[9] Then, for every subgroup conditioning on (i) and (ii), we study their respective empirical distributions.

[8] The use of log income implicitly drops observations with zero labour income. To address this problem, we recalculate all our moment estimates using the Arc-Percent Change method which is the mid-point average of changes of individual-to-group income ratios. The group income is the average income by subgroup of interest (e.g., age cohort and income history). In other words, $\Delta^n_{\hat{\mu}^{arc}_{i,t}} = \dfrac{\hat{\mu}^{arc}_{i,t} - \hat{\mu}^{arc}_{i,t-n}}{(\hat{\mu}^{arc}_{i,t} + \hat{\mu}^{arc}_{i,t-n})/2}$ where $\hat{\mu}^{arc}_{i,t} = \dfrac{y_{i,t}}{\bar{y}_t}$. We do not find any significant differences and conclude that our results are robust to the inclusion of zero income.

[9] When $n = 1$, the past or previous period income refers to last year income. When $n = 3$, the appropriate previous period income is the average income of the past 3 years. Since we do not have a longer time series covering the entire life cycle of individual observations, the setup allows us to understand what the dynamics of individual earnings and household income look like at different points of life. In other words, it tells us the average experience with regards to earnings risk and insurance of someone who belongs to the intersection of a particular age and income group. Because the reliability of estimates for each subgroup depends on the size of observations, we limit our study to just four age cohorts and income decile.

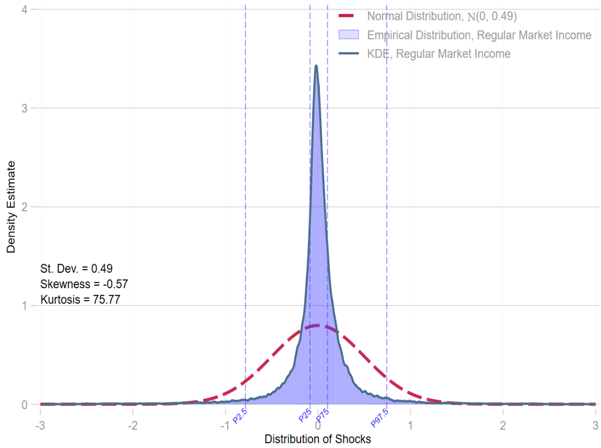

Figure 1: **Empirical distribution of annual growth ($\Delta^{n=1}_{\widehat{\mu}_{i,t}}$) of individual regular market income for primary earners aged** $25-64$.
Notes: A corresponding distribution of 3-year average income growth ($\Delta^{n=1}_{\widehat{\mu}_{i,t}}$) is reported in Figure F.1 in the appendix.

Higher-order moments. We characterize the distribution of income shocks using second- and higher-order moments: (a) *Variance*, (b) *Standardized (Pearson) Skewness*, and (c) *Standardized (Pearson) Kurtosis.*

To better understand the dynamics of income process and draw a distinction between parametric and nonparametric methods in deriving the higher-order moments of shocks, consider first a parsimonious permanent and transitory component model for the equation 1

$$\widehat{\mu}_{i,t} = z_{i,t} + \epsilon_{i,t}$$

where $z_{i,t}$ is the permanent component which follows a random walk such that $z_{i,t} = z_{i,t-1} + \eta_{i,t}$, and $\epsilon_{i,t}$ is the transitory component. The permanent ($\eta_{i,t}$) and transitory ($\epsilon_{i,t}$) innovations are drawn from distributions $F_\eta \sim \left(0, \sigma^2_\eta\right)$ and $F_\epsilon \sim \left(0, \sigma^2_\epsilon\right)$, respectively. Note we do not restrict the innovation terms to be drawn from normal distributions. Accordingly, we can compute $n-$year log income growth

$$\Delta^n_{\widehat{\mu}_{i,t}} = \widehat{\mu}_{i,t} - \widehat{\mu}_{i,t-n} = \sum_{j=t-n+1}^{t} \eta_{i,j} + \epsilon_{i,t} - \epsilon_{i,t-n}. \tag{2}$$

This implies that the income shock process (or earnings risk) is driven by the permanent ($\eta_{i,t}$) and transitory ($\epsilon_{i,t}$) innovations. Accordingly, let σ_x, S_x and K_x denote the standard deviation, skewness and kurtosis of distribution F_x, $x \in \{\eta, \epsilon\}$, respectively. Given the parametric model defined in Equation 2, we can compute the second to fourth moments of the $n-$year log income growth $\Delta^n_{\widehat{\mu}_{i,t}}$ analytically

$$\begin{aligned}
\sigma^2_{\Delta^n_{\widehat{\mu}_{i,t}}} &= n\sigma^2_\eta + 2\sigma^2_\epsilon \\
S_{\Delta^n_{\widehat{\mu}_{i,t}}} &= \frac{n\times\sigma^3_\eta}{\left(n\times\sigma^2_\eta+2\times\sigma^2_\epsilon\right)^{\frac{3}{2}}} S_\eta \\
K_{\Delta^n_{\widehat{\mu}_{i,t}}} &= \frac{n\times\sigma^4_\eta}{\left(n\times\sigma^2_\eta+2\times\sigma^2_\epsilon\right)^2} K_\eta + \frac{2\times\sigma^4_\epsilon}{\left(n\times\sigma^2_\eta+2\times\sigma^2_\epsilon\right)^2} K_\epsilon
\end{aligned}$$

The previous literature assume that the permanent and transitory innovation terms are drawn from normal distributions $N_\eta \sim (0, \sigma_\eta^2)$ and $N_\epsilon \sim (0, \sigma_\epsilon^2)$, respectively. This implies that $\Delta^n_{\widehat{\mu}_{i,t}}$ follows a normal distribution $N_{\Delta^n_{\widehat{\mu}_{i,t}}} \sim (0, n\sigma_\eta^2 + 2\sigma_\epsilon^2)$. For example, Chatterjee, Singh and Stone (2016) employs this approach to estimate the random-walk permanent/transitory model for Australia. If we use similar assumptions and moment conditions, we can estimate σ_η and σ_ϵ and work out $\sigma_{\Delta^n_{\widehat{\mu}_{i,t}}}$, $S_{\Delta^n_{\widehat{\mu}_{i,t}}}$, and $K_{\Delta^n_{\widehat{\mu}_{i,t}}}$ accordingly.

However, we take a different (nonparametric) approach as in Guvenen et al. (2021) and directly calculate the second- and higher-order moments of income shocks. That is, we calculate the group–specific shocks via

$$\tilde{\mu}_z^k = \mathbb{E}\left(\frac{z-\mu_z}{\sigma_z}\right)^k \tag{3}$$

where z denotes $\Delta^n_{\widehat{\mu}_{i,t}}$, μ_z denotes $\mathbb{E}(z)$ and $\tilde{\mu}_z^k$ denotes the k^{th} standardized moment of z. This approach allows us to test the Gaussian and linear shock assumptions in addition to identifying the sources behind the non-normalities and non-linearities.

For comparability with the literature, we also document quantile-based measures of skewness and kurtosis, namely,

$$Kelley's\ Skewness = \frac{(P_{90}-P_{50})-(P_{50}-P_{10})}{P_{90}-P_{10}}$$

and

$$CrowSiddiqui\ Kurtosis = \frac{P_{97.5}-P_{2.5}}{P_{75}-P_{25}}.$$

3 Results

In this section, we present two sets of main findings. We discuss the dynamics of earnings, wages, and hours of primary earners by age group and past income decile in subsection 3.1. We turn to the role of family and government in subsection 3.2.[10]

3.1 Second and higher-order moments

3.1.1 Dispersion

Figure 2 reports second moment statistics of average earnings, wage, and hour changes by earnings history of employees who are primary earners with consistent work history.

There are common features between the left and right panels which respectively show the variances for annual and 3-year average changes. First, the variances of earnings, wage and hour changes are especially pronounced for the bottom-most decile, more than twice those of the remaining income groups. That a similar pattern can still be observed for the 3-year average changes, though to a much smaller extent, suggests that the poorest labour income earners face more persistent second-order risks. While primary earners in the top decile do experience a somewhat larger dispersion in their earnings and wage changes, the difference to those in the upper lower and middle income brackets is trivial. Second, wage changes play a markedly bigger role in explaining earnings fluctuations, except

[10] Supplementary analyses on (i) the self-employed, and (ii) the permanent and full-time employees are provided in appendix C and D.

for the bottom decile whose changes in hour and wage exert virtually equal influence sizewise on the variance of annual earnings changes. The fact that a large proportion of part-time ($\approx$50%) and casual ($\approx$30%) workers in the sample belongs to the bottom decile helps account for their higher variance of hour changes. We find similar relationships across subsamples.[11] Third, the large negative covariance $COV(\Delta w, \Delta h)$, particularly for the lower past income deciles, suggests a strong negative income effect. In other words, low-income primary earners encountering adverse wage shocks make up for the loss by significantly increasing their work hours.[12]

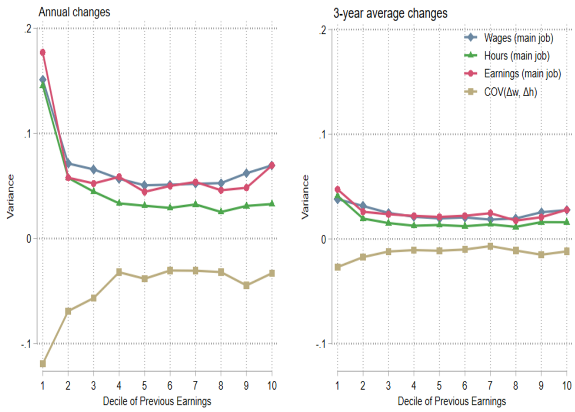

Figure 2: **Variances of average changes in regular earnings, wages and hours of primary earners.**

There are also notable differences between the annual and 3-year statistics. The latter's variance undergoes a substantial decline, most strikingly for the bottom past income decile. As a result, the second-order persistent earnings risk (associated with the 3-year average statistics) falls precipitously for the lowest decile to a comparable level with their higher income counterparts. For the rest of the income group, the variance of hour changes diminishes by a lesser extent compared to that of wage changes, but wage changes still contribute more to the fluctuations of their 3-year average earnings changes. In addition, the right panel displays a significant shrinkage of income effect as reflected by the lesser wage-hour covariance magnitude for persistent risk.

Knowing that the earnings shock fluctuation is more strongly associated with the wage process does not inform us about how wages and hours explain different directions and sizes of earning changes. Figure 3 thus complements the above findings by illustrating that: (i) wage changes constitute the main driving force behind earnings changes, especially for the upward movement, (ii) hour changes are more important for low income groups, and (iii) there exists asymmetry between positive and negative earnings changes with respect to their contributing factors.

The annual statistics of Figure 3 show that, apart from the bottom decile, wages contribute substantially more to the movement in earnings, whereas the contribution by hours is either small or absent. For the fifth and ninth deciles, hours contribute solely to negative earnings changes, though their role is still limited relative to that of wage changes. In contrast, for the poorest, hour changes contribute about as much as wage changes do to large earnings fluctuations.

[11] In Appendix D, we demonstrate that removing part time and casual employees from the sample significantly weakens the role of hours in driving the earnings dynamics of low income earners.

[12] We provide more dispersion statistics in the appendix. Figure F.2 and F.3 report second moment statistics of annual and 3-year average earnings, wage and hour changes by selected subsamples. Table A.3 and A.4 are cross-tabulations on part-time and casual employment by age cohort and past decile of usual weekly earnings from main job.

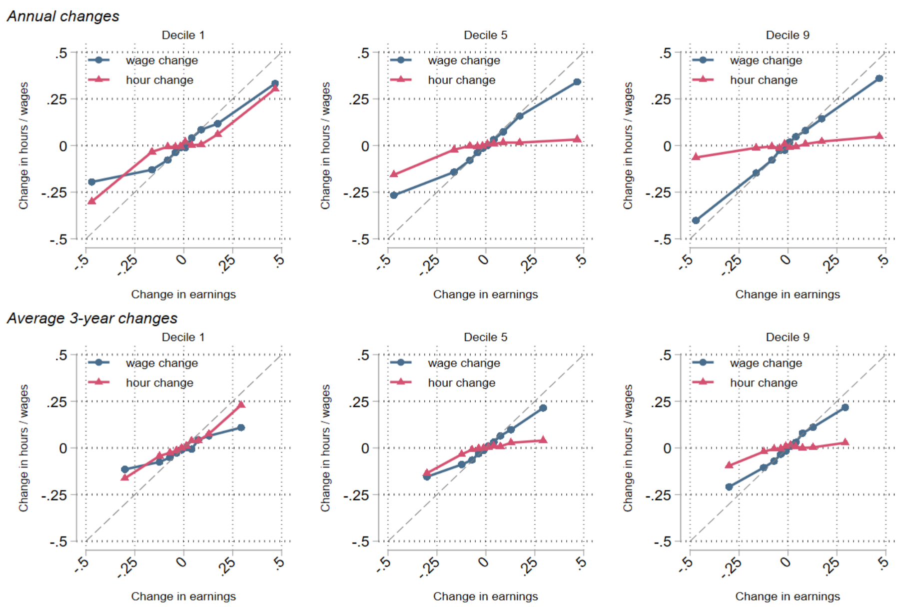

Figure 3: **Average changes in residual regular wages and hours versus changes in residual regular earnings.**

Notes: These are results for primary earners (main job) in the 1st, 5th, and 9th deciles of past regular weekly earnings. The top and bottom panels report annual and 3-year average changes, respectively.

A critical distinguishing factor between the annual (*top panel*) and the 3-year (*bottom panel*) average statistics in Figure 3, aside from the smaller extremes, is the stronger earnings-hour correlation of the latter. As depicted in the bottom-left graph for primary earners in the lowest past income decile, hour changes are dominant in driving extreme earnings changes on both ends. For example, at their highest positive (*negative*) earnings changes of 0.30 (-0.30) log points, the corresponding average hour and wage changes are around 0.25 (-0.18) and 0.125 (-0.12) log points, respectively. Likewise, for the median and top income earners (bottom-middle and bottom-right graphs), their 3-year average changes in hours explain a greater proportion of the fall in earnings, particularly at the extreme. On the positive side, however, the top and the bottom panels show almost no divergence with respect to the relative shares of hour and wage changes in accounting for earnings changes of the two income groups.

The above indicate that for the middle and upper income primary earners, transitory and persistent earnings changes are largely determined by wage changes. The role of hours is negligible on the positive side, but it does explain a small to moderate fraction of large falls in their earnings. These results are consistent with the rising variance of log hourly wages and persistent component of wage shocks over time and over life cycle as documented in Chatterjee, Singh and Stone (2016); Kaplan, Cava and Stone (2018); Freestone (2018). However, they deviate from the previous findings for other OECD countries where hours take either a dominant or an equal role in driving the earnings dynamics (see De Nardi et al. (2021) for the US and the Netherlands and Halvorsen et al. (2020) for Norway). The institutional features of the laws and regulations surrounding wages and work hours in Australia, including the national minimum wage and the national employment standards (NES), might have generated rigidity along the intensive margin of labour supply, making it hard for both employers and employees to adjust non-casual hours up. More specific examples are the high extra remuneration for overtime work and the legal arrangement that permits annual leave to be accrued on overtime hours (abolished in 2009).[13] In consequence, it is unlikely that full-time workers can increase their earnings by working longer hours than they already do. The labour market structure that influences job and career mobility - voluntary or involuntary - may also play a role in raising the influence of wages on earnings growth. Conversely, there are fewer barriers when hours fall due to, for instance, early retirement, health shock and unemployment spells that are either less or not constrained by the hour cap or the institutional friction.

Quite the contrary, the earnings dynamics of employees in the bottom decile behave differently. Hour changes contribute roughly as much as wage changes do to the changes in their earnings. As a large portion of this group works in casual and/or part-time employment, they are subject to fewer regulations and have a greater degree of freedom to adjust their hours. This group is also more likely to be underemployed or unemployed temporarily, which implies that the perceived changes in usual work hours may also involve some information on the extensive margin.[14]

Lastly, some caveats apply in interpreting the results. As wages are derived from usual weekly work hours and earnings, measurement errors arise because of the loss of information pertaining to short-term unemployment spells and other irregularities affecting work hours within each year of observation. The exclusion of workers with inconsistent employment history helps alleviate the problem, but the strict sample selection criteria come at some cost of information on the extensive margin. This finding therefore applies primarily to the intensive margin of labour supply. That said, assuming independent measurement errors, the errors would have to be large to explain away the observed pronounced differences in hour and wage contributions. Note too that, relaxing the sampling restriction brings about a greater relationship between negative hour and negative earnings changes, and in this sense, enlarges the role of hours in explaining the earnings shock dispersion. Nonetheless, it does not change the result with regards to the non-existent impact of hours on upward movement in earnings, nor does it alter the fact that wage changes play the biggest role in producing the second-order earnings risk.[15] On this ground, we expect the inclusion of more extensive margin information (e.g., with high-frequency administrative data) to reduce the measurement errors and expand the role of hours in explaining the downward movement of earnings.

3.1.2 Skewness and Kurtosis

Figure 4 reports higher-order moments of earnings shocks. As seen in the top panel, except for workers in the bottom decile, the distribution of usual weekly earnings shocks is highly left skewed with its magnitude being an increasing function of past weekly earnings. In more colloquial terms, negative or left skewness means extreme negative earnings shocks are more severe compared to positive ones. The corresponding 3-year average changes are more symmetric although primary earners in the upper four past income deciles still experience a relatively high negative skewness. This implies that upper income individuals are affected by more extreme persistent adverse shocks to their earnings.

It is apparent that both the distributions of annual and 3-year average hour changes are considerably more left skewed than those of earnings changes while the opposite is the case of wage changes.[16]

[13] More information on overtime pay in Australia can be found on FairWork Ombudsman's website.

[14] We only have access to report on their employment status at the annual frequency. Even with the stricter sample selection criterion on work history, it is highly improbable that we were able to fully exclude those unemployed over a short time span within a year.

[15] See Figure F.4 in the appendix.

[16] Results are consistent across the various household characteristics we examine. See Figure F.5 and F.6 in the appendix for the third-moment statistics of annual and 3-year average earnings, wage, and hour changes by selected

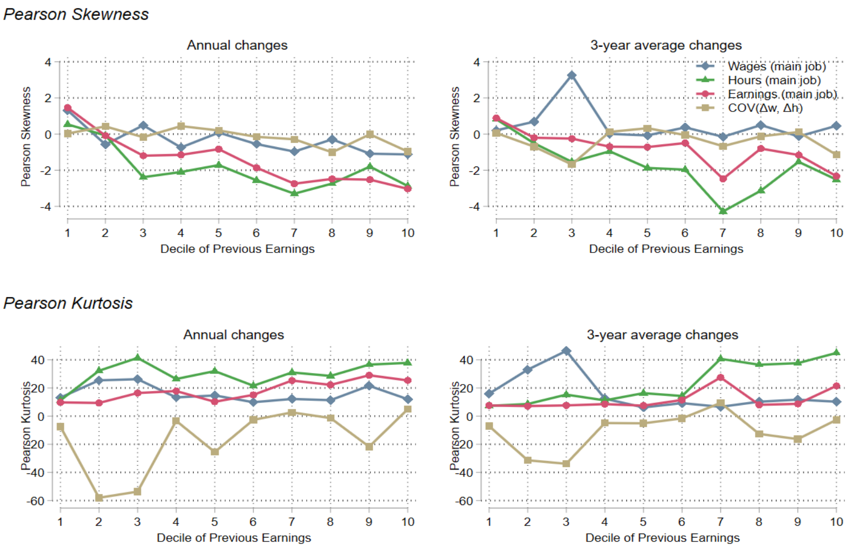

Figure 4: **Pearson Skewness and Pearson Kurtosis of average changes in regular earnings, wages and hours of primary earners.**

These estimates demonstrate that the third-order earnings risk is driven by hours. In addition, we see that co-skewness of the annual changes tends to hover around zero, while the co-skewness of the 3-year average changes is more on the negative side. Negative co-skewness reflects the interaction between wage and hour changes, how a fluctuation in one tends to be accompanied by a decrease in the other. Since the second-order risk associated with wages is relatively high, the volatility of wage changes is the primary determinant of co-skewness. In this regard, negative co-skewness means large wage fluctuations are often associated with declines in hours, which add to the adverse earnings shocks. This explains why the co-skewness in Figure 4 moves in tandem with the skewness of earnings changes, though its influence is small compared to that of hours.

The findings conform to our earlier understanding. Earnings shocks have more room downward than upward. Being in full-time employment, to say nothing of the various institutional restraints, naturally places a hard upper bound on hours. Prior quantitative investigations suggest the nature of job ladder as a strong candidate explaining the role of hours in driving the third-order earnings risk. In particular, Lise (2012) shows how workers at the top of the wage distribution faces job-loss risk while those at the bottom climb the ladder slowly with the arrival of job opportunities and the incremental wage gains. Similarly, Huckfeldt (2018) finds that job loss leads to occupation displacement for some workers who are forced to search in the lower skilled labour market. In Australia specifically, workers experiencing job loss could be absorbed and become entrenched in its large part-time and casual employment industries. These factors might help account for the observed third-order hour and earnings risks of the upper income earners. For further discussion, see appendix D.[17]

subsamples.

[17] In appendix D, we show that removing casual and part-time employees from the sample leads to hours (wages) having a much weaker (stronger) influence on the 3rd-order earnings risks but does not diminish the magnitude of transitory earnings risk. This evidence, though incomplete, points in the direction of Lise (2012). It seems that most of the observed transitory 3rd-order earnings risk belongs to permanent and full-time employees. This in turn is driven by wage changes which can be interpreted as job loss and relocation to lower skilled industries, though we cannot rule out other factors such as voluntary job switching. For Australia, in particular, the third-order risk is not persistent for full-time and permanent workers. The entrenchment story of Huckfeldt (2018) does not seem to hold in this case.

The bottom panel of Figure 4 depicts shock distributions with excess kurtosis (leptokurtic). A leptokurtic distribution is denser around the centre (high peakedness) and thicker at the tails than the standard Gaussian distribution. The large kurtosis (i.e., the fourth-order risk) thus implies that changes in earnings are rare and most are small, but at the extreme, they occur more frequently. To put it differently, most breadwinners seldom encounter any large changes to their earnings, but the probability of experiencing drastic earnings changes is greater than otherwise prescribed by the standard Gaussian distribution. The figure shows that the fourth-order earnings risk is driven primarily by the large positive kurtosis of hour changes. As an example, except for those in the lowest decile, although both wage and hour kurtoses contribute to the excess kurtosis of annual earnings changes, the contribution by hours is approximately twice as much.

The impact of hour changes on the fourth-order earnings risk is dampened to an extent by the negative co-kurtosis, a counterbalancing force. Co-kurtosis between two random variables captures the relationship between extreme changes of one variable and deviation of the other. They can also be understood as the likelihood that two random variables undergo either positive and negative drastic changes together. The negative co-kurtosis thus suggests that an extreme decrease (*increase*) in wages tends to be offset by an increase (*decrease*) in work hours. This interaction reduces the otherwise high density at the centre and tailends of the annual earnings shock distribution, thereby mitigating the fourth-order earnings risk to a relatively moderate level. For more persistent changes (bottom-right panel), the effect size of hours shrinks for the lower six deciles, though its contribution to the fourth-order earnings risk remains strong for the upper four deciles.

In short, despite the dominance of wage changes in driving the second-order earnings risk, our third and fourth moment estimates in Figure 4 show that hour changes constitute the principal source behind the higher-order earnings risks. Results concerning the role of wages and hours in accounting for earnings dynamics thus far are qualitatively robust across the different household characteristics examined.

Thus, our findings indicate that the distribution of earnings shocks displays negative skewness and excess kurtosis, deviating from the conventional linearity and normality assumptions. There is variation in the sources of earning shocks. Wage changes are strongly associated with earnings changes and account more for the dispersion of earnings shocks; meanwhile, the contribution of hour changes is largely absent in upward movement and relatively small in downward movement of earnings changes. In our extension in Appendix E, we estimate a parametric model of earnings dynamics with non-linearity and non-normality assumptions. We find that our estimated Non-Gaussian model can reproduce the pattern of the key empirical facts.

3.2 Insurance against earnings shocks

In this section we study the extent to which earnings risk is mitigated by implicit and explicit forms of insurance arrangement. For this purpose, we use the regular market earnings which is a broader income definition comprising earnings from all market sources instead of labour earnings. We begin with a brief comparison of the second-order earnings risks faced by different age cohorts. We next report the role of family and government insurance in part 3.2.1 and 3.2.2, respectively.

Note that, we relax the previous section's sampling restriction and include all employees regardless of their employment history in this section. In addition, we consider robust moment statistics P1-P99, P5-P95, and P10-P90 to address potential outliers that may arise due to the broader sampling criteria.

Nonetheless, the non-robust and robust statistics only differ quantitatively while the qualitative patterns persist across settings. We chose to present the P1-P99 figures in the main paper only for ease of interpretation, conciseness and aesthetic. For higher-order moments, the discussion revolves around the Pearson measures of skewness and kurtosis (i.e., the standardized third and fourth moments) of the income shock distributions instead of the quantile-based robust skewness and kurtosis (i.e., Kelley's Skewness and Crow-Siddiqui Kurtosis).[18] This is to ensure an acceptable degree of robustness without sacrificing too many observations at the tails of the distributions that contain information crucial for understanding of family and government insurance against higher-order risks.

3.2.1 Family insurance

Figure 5 displays standard deviation statistics of the shock distributions for annual (*left panel*) and 3-year (*right panel*) average regular market income, both of which have U-shaped income profiles for all age cohorts (25-64) with the greatest dispersion for primary earners whose past regular market income lies in the lowest decile. Top earners also experience a relatively strong fluctuation, but the magnitude is considerably smaller than those of the bottom decile. The high share of low income earners employed in part-time and casual jobs that entail more irregular hours, seasonality, and risk of layoff is one potential reason.

There are notable differences between the two panels. First, excluding the bottom decile, we see a small non-uniform decrease in the second-order persistent earnings risk associated with the 3-year statistics for all cohorts. Second, for workers in the bottom-most decile in particular, the fluctuations of their 3-year average market earnings changes are substantially smaller compared to those of their annual changes. The drop is even more drastic for the younger cohorts.

A closer inspection further shows that the distributions of earnings shocks of the two middle age cohorts ($35 - 44$ and $45 - 54$) are predominantly less dispersed compared to those of the youngest and the oldest. Career/job switching and pursuit of higher education are possible causes of the more volatile shocks for the young. Health shock and early retirement are more prevalent among members of the oldest cohort ($55 - 64$). However, for the middle cohorts who are in the prime age of carrying family responsibilities (e.g., raising children), these events are less likely. In turn, when compared to the oldest, the youngest experiences higher transitory and persistent fluctuations, especially if they happen to be below the median past income. This implies that the process driving the second-order earnings risk for the youngest group is more potent and persistent. Loosely speaking, a plausible explanation is that job/career mobility and other early life events can result in either adverse or favourable earnings growth and therefore more variation, whereas health status deterioration and early retirement in later life cycle only lead to decline (a unidirectional change) in market earnings and thus less variation. Similar results are observed across the different measurements of second-order risk.[19]

A logical follow-up question to the prior discussion is to what extent does family income insure primary earners against their market earnings risks. To answer this question, we first compare the standard deviation of individual market income with that of their family market income to capture *family market income insurance*. Then, private transfers from non-resident family members are added

[18] For comparability with the literature, Kelley's and Crow-Siddiqui figures are included in the main section of the paper, though not elaborated. P5-P95 statistics are reported in the appendix. We do not present P10-P90 statistics due to space constraint.

[19] See Figure F.9 and F.10 in the appendix for more detail.

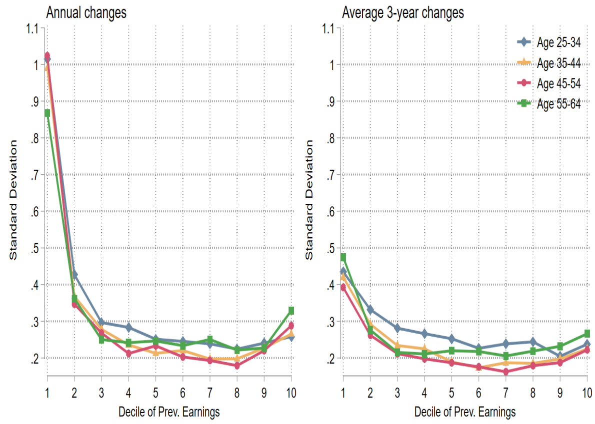

Figure 5: **Standard deviation of the distribution of regular market earnings shocks for primary earner (P1-P99)**.

to family market income to derive total family pre-government income. We define the extent by which the standard deviation of this new measure falls below that of the family market income as *family private transfer insurance*.

Evidence from Figure 6 reveals that the insurance effect of family market income and private transfer against the second-order individual market income risk is little to none. This is unexpected. The top panel demonstrates that family insurance only applies to those situated in the bottom past income decile, and only family market income matters while the addition of private transfer marginally raises the level of dispersion. Even this small family market income insurance for the poorest dissipates completely when we consider the more persistent 3-year average shocks. In fact, the bottom panel indicates that family earnings and private transfer actually elevate the second-order risk.

The absence of family insurance implies dominance of the *income-pooling effect* of family as opposed to the *added-worker effect*.[20] That is, family members do not actively adjust their market activities (e.g., labour supply) in response to primary earner's earnings shocks. As a result, earnings from secondary earners tend to increase the variance of combined family market income.

Next, in order to learn about family insurance against the higher-order risks, we perform the same pairwise comparison on skewnesses and kurtoses of the distributions of primary earner's own market income, family market income and family pre-government income.

Figure 7 conveys more revealing information. As it turns out, the above passiveness of family members only applies to small and moderate shocks. Family income is still paramount to insuring against the third- and fourth-order market earnings risks. Secondary earners appear to respond to extreme adverse earnings shocks of primary earners.[21] The top panel of Figure 7 shows large negative skewness (between -1.0 and -2.5) for primary earners in the upper nine deciles of the past market income distribution across all age groups. Evidence from Figure 4 points to hour changes as the

[20]The variance of family income changes is given by $VAR(\Delta f) = f_p^2 VAR(\Delta p) + \overbrace{f_s^2 VAR(\Delta s)}^{\text{income-pooling effect}} + \underbrace{2 f_p f_s COV(\Delta p, \Delta s)}_{\text{added-worker effect}}$, where f_p and $f_s = 1 - f_p$ are income shares of the primary and secondary earners, respectively; $f_p^2 VAR(\Delta p)$ is the contribution of primary earner's earnings shock variance; $f_s^2 VAR(\Delta s) > 0$ is the contribution of secondary earner's shock variance (*income-pooling effect*); $2 f_p f_s COV(\Delta p, \Delta s)$ is the contribution of the covariance (*added-worker effect*). See subsection B.2 of the appendix for further explanation.

[21]The observed insurance effect against higher-order earnings risks is generally consistent across all the subsamples analyzed. Thus, we report the annual statistics and leave the rest in the appendix.

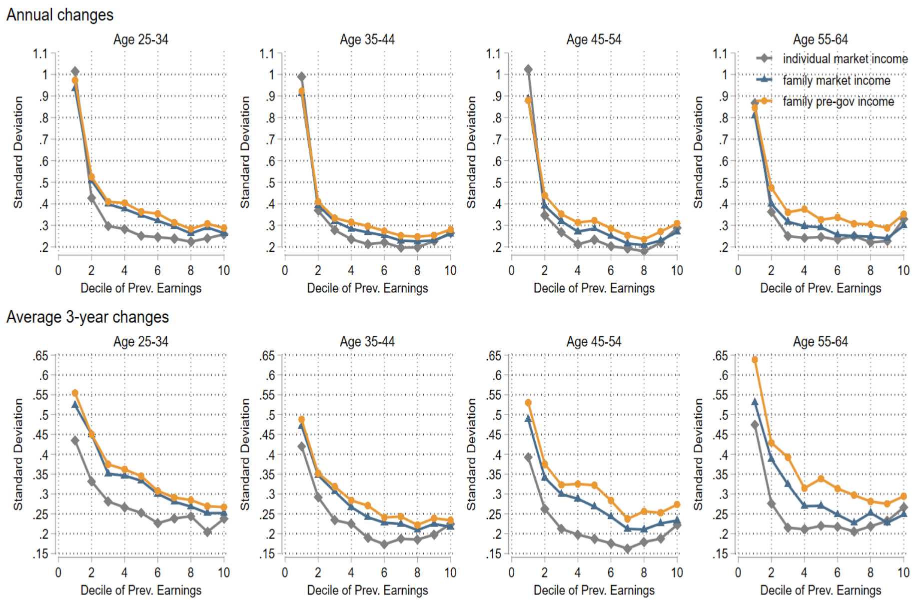

Figure 6: **Standard deviation of the distribution of annual and 3-year average changes of family income by decile and age.**
Notes: The figure shows the relative contribution of family market income and private transfer to the second-order risk of family pre-government income.

main driver. Under this scenario, family market income provides substantial insurance, resulting in remarkably lower negative skewnesses (ranging between -0.5 and -1.5) compared with those of the individual income shocks. Better-off households (at or above the median past earnings) from the oldest age cohort $(55-64)$ also benefit from moderate private transfer insurance, supplementing the market income adjustment by their members. In fact, the presence of private transfer allows the third-order pre-government income risk of the richer seniors to arrive at a similar level as those of the younger cohorts who rely exclusively on their family market income insurance.

The sole outlier is the bottom-decile primary earners whose skewness is strongly positive. As aforementioned in subsection 3.1.2, the bottom decile earners have more room upward than downward. More flexibility and opportunities for growth of hours and wages could help account for the observed dynamics.

Kurtosis of the earnings shock distribution also manifests non-Gaussian and non-linear properties. According to the lower panel of Figure 7, kurtosis is large and positive (leptokurtic) with a somewhat hump-shaped income-profile for all age cohorts. Its minimum is around 5 which is still well above the standard normal kurtosis value of 3. Like skewness, kurtosis statistics in Figure 4 suggest hours to be the main explanatory factor. Moreover, since annual level earnings changes may involve short-term unemployment spells, they likely augment the influence of hours. As for insurance against the fourth-order individual earnings risk, the mitigating effect of family market income is significant, enough to reduce the kurtosis levels for all households to comparable degrees (between 5 and 7). The only exception is for the bottom decile primary earners whose kurtosis is already small to begin with. Again, the ability to adjust one's hours for casual and part-time employees in response to shocks could partly explain the relatively smaller fourth-order risk of those in the lower past income deciles.

We also compute Kelley's skewness and Crow-Siddiqui kurtosis.[22] The Crow-Siddiqui kurtosis

[22] Figures F.11 to F.25 in the appendix show the corresponding P1-P99 and P5-P95 standardized and quantile-based

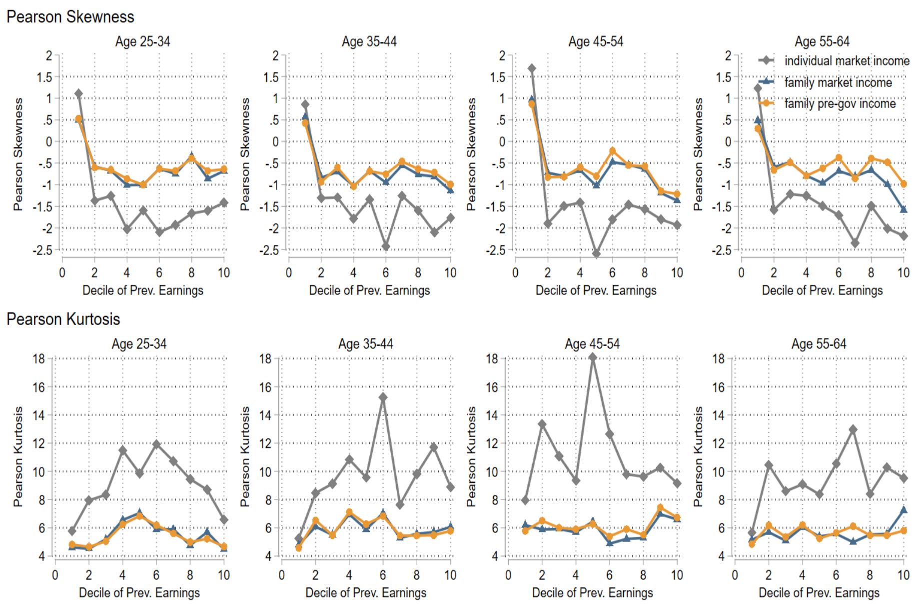

Figure 7: **Skewness and Kurtosis of the distribution of annual changes of family income by decilde and age.**

Notes: The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of family pre-government income. Corresponding moment statistics for 3-year average changes show similar patterns and are provided in subsection F.2 of the appendix.

behaves more erratically compared with the Kelley's skewness statistics, though the hump-shaped income profile and the family insurance effect can still be observed. In contrast, Kelley's skewness exhibits more consistent patterns across the different measurements. It demonstrates that once enough extreme shocks at the tailends have been excluded, the shock distributions for those below the median lean rightward and the upper deciles shock distributions lean leftward. The distribution of shocks however become fairly symmetrical. This confirms that the third-order risk is really the story of the lower and upper 10% whom the Kelley's skewness ignores. Additionally, it highlights the fact that extreme shocks in either direction (i.e., adverse or favourable) bring about family responses. Not only do family members increase their market activities in response to severe downward shocks, the Kelley's skewness statistics indicate that they also react to large positive shocks by cutting back their own market activities.

In a nutshell, it appears that extreme shocks induce responses from family. For a typical employee - who is also the primary earner of their household - in Australia, their family market income serves as a crucial source of insurance against the third- and fourth-order earnings risks even if it does not mitigate the second-order risk.

3.2.2 Government insurance

We now turn to the role of government insurance provided via progressive taxes and transfers - *government tax insurance* and *government transfer insurance* - against the second- and higher-order risks of family pre-government income. For our purpose, government tax insurance is defined as the extent to which combined family income taxes reduce the second- and higher-order risks of family pre-government income. Analogously, government transfer insurance is the extent to which public

statistics of the annual and 3-year average changes calculated using (i) the standard method from equation 1, and (ii) the Arc-Percentage Change method.

transfers can fulfill the same task. We capture the former by the gap between moment statistics of family pre-government income and post-tax (pre-transfer) income, and the latter by that between family post-tax income and family post-government income.

Figure 8 depicts the effect of government insurance in mitigating the dispersion of shocks (or second-order risk). Based on annual change statistics in the top panel, though tax insurance is trivial, government transfer considerably decreases the second-order risk of family pre-government income for primary earners below the median past market income.[23] The insurance is at its largest for the poorest households and declines rapidly as one moves up the income hierarchy. A noteworthy observation is that relative to the annual statistics, government transfer insurance against persistent second-order risk remains significant (bottom panel of Figure 8). For the bottom decile, the magnitude of insurance may have declined but not in a relative sense. This is most likely a product of the targeted and means tested welfare programs such as the family-oriented social securities from which families receive pecuniary support (with large base and maximum payments) conditional on the number of dependent children and the combined family income level. Thus, government insurance is effective against both transitory and persistent second-order risks. However, it may also be a sign that households rely too heavily on public transfers, and that the presence of strong government insurance influences behaviour and consequently the persistence of income risk.[24]

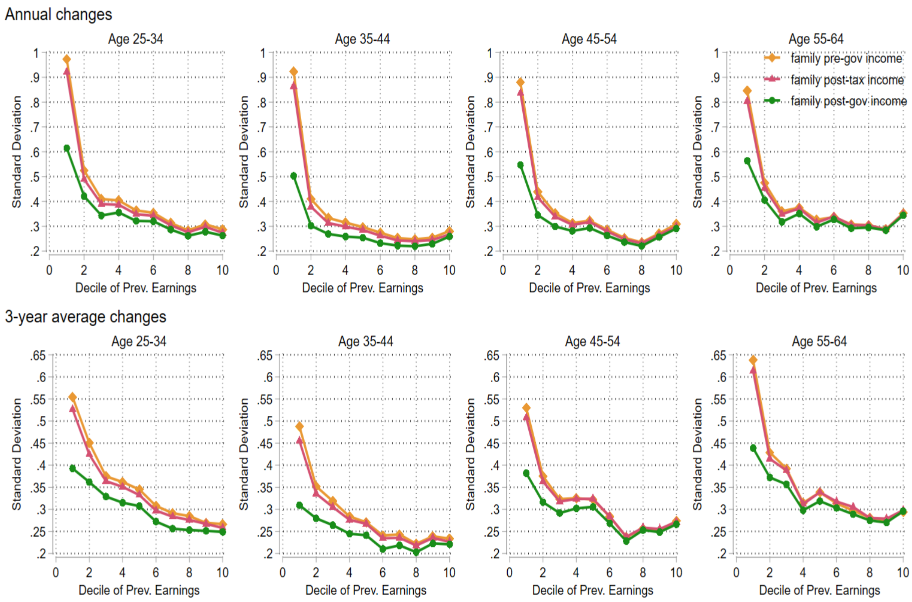

Figure 8: **Standard deviation of the distribution of average changes of family income by income decile and age.**

Figure 9 shows the relative contributions of tax and transfer to the third-order risks of annual (*top panel*) and 3-year (*bottom panel*) average family disposable income. Given the large family insurance against extreme shocks, it is to be expected that the government insurance is relatively small. Still, government transfer insurance against the third-order risk at the annual level is visible and non-trivial for most households, especially those of the younger two cohorts. For the 3-year average changes, the

[23]This occurs because by construction, public transfer and family pre-government income move in opposite direction. That is, $COV(income, transfer) < 0$.

[24]See Figure F.26 to F.28 in subsection F.3 of the appendix for the corresponding P1-P99 and P5-P95 second moment statistics of the annual and 3-year average changes calculated using (i) the standard method in equation 1, and (ii) the Arc-Percentage Change method.

insurance remains sizeable for the youngest but largely disappears for the older cohorts.

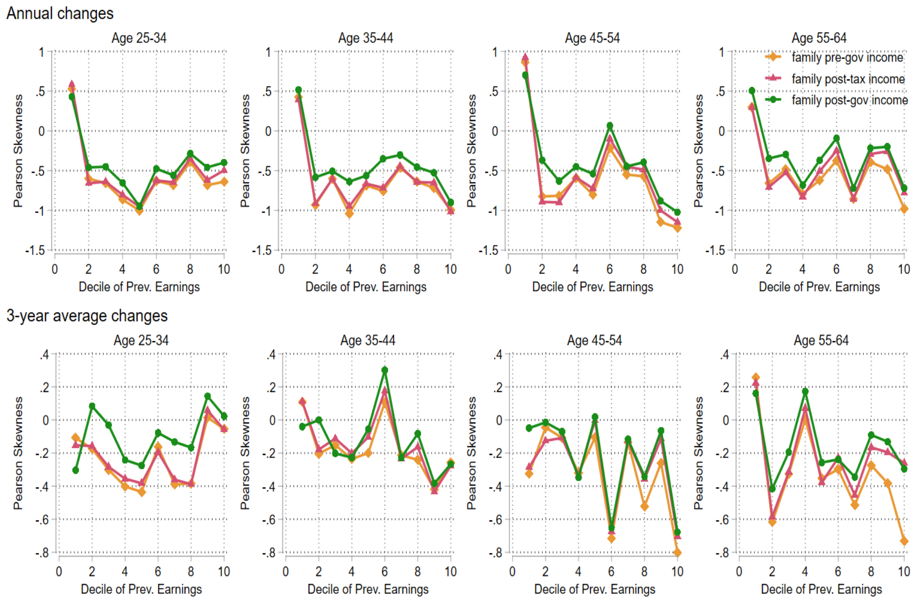

Figure 9: **Skewness of the distribution of average changes of family income by income decile and age.**

The annual statistics on the top panel of Figure 10 reveal that government tax and transfer insurance against the fourth-order family pre-fiscal income risk is generally absent. Likewise for the 3-year average changes on the bottom panel, government tax and transfer play no insurance role; on the contrary, they could lead to more excess kurtosis for some households.[25]

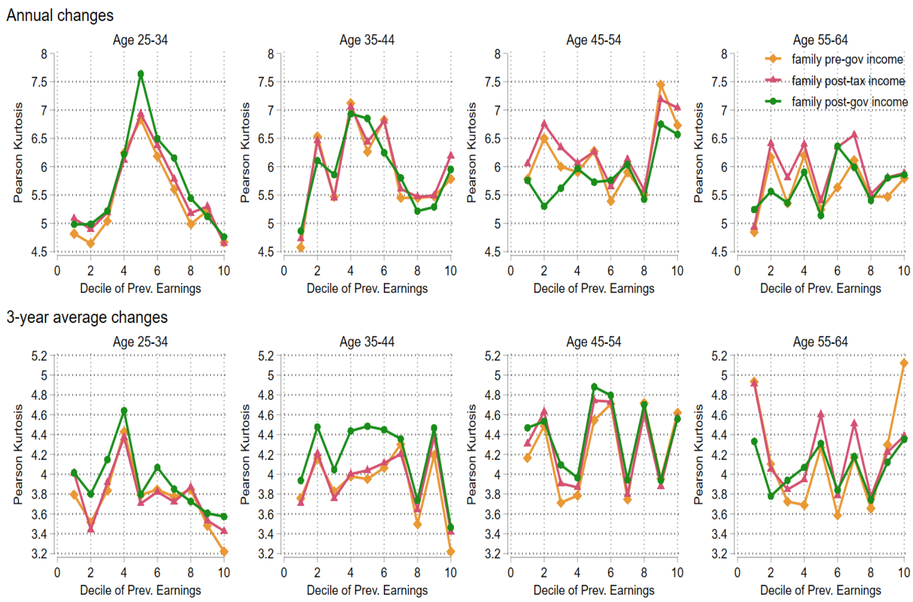

Figure 10: **Kurtosis of the distribution of annual and 3-year average changes of family income by income decilde and age.**

[25] See Figure F.29 to F.44 in subsection F.3 of the appendix for corresponding P1-P99 and P5-P95 third and fourth moment statistics of the annual and 3-year average changes calculated using (i) the standard method in equation 1, and (ii) the Arc-Percentage Change method, which show mostly consistent results with the findings in this subsection.

3.2.3 Spousal response versus government transfer

One of the key lessons from the previous section is that government transfer is an important source of insurance against income shock volatility while family market income insurance is most potent against extreme shocks. To explore this result further, we construct two additional figures (aggregated over age) to learn more about primary earner's earnings shocks and their correlations with changes in spouse's market earnings and public transfer.

Figure 11 plots spouse's average weekly wage and hour changes against changes in weekly earnings for primary earners grouped by their past income rank. In the top panel, we see that annual changes in work hours and wages of spouse in response to primary earner's earnings shocks are largely absent. As Figure 11 is based on usual weekly work hours and wage rates, one may argue that some fluctuations within a year such as temporary unemployment of primary earners and employment of their partners are omitted, which could explain the absence of spousal response. However, the fact that the 3-year average statistics (the bottom panel) still show no sign of any sizeable or consistent spousal response corroborates our earlier hypothesis that market activity adjustment on the part of spouse is indeed lacking.[26]

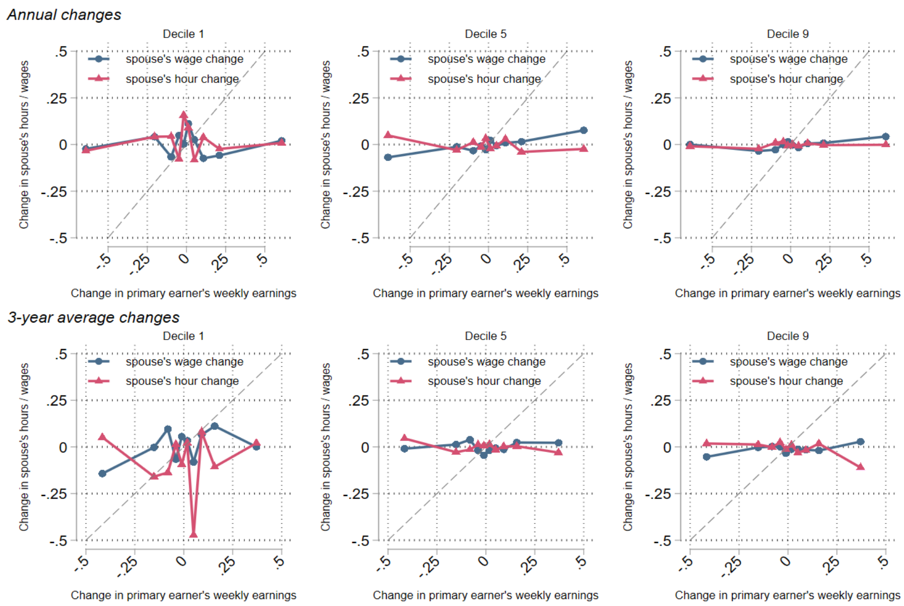

Figure 11: **Changes in weekly wages and hours of spouse versus decile of changes in weekly earnings**. *Notes:* These are results for of primary earners (main job) in the 1st, 5th, and 9th deciles of past weekly earnings. The top and bottom panels report statistics of annual and 3-year average changes, respectively.

Figure 12 compares changes in annual spousal earnings and public transfer against changes in primary earner's annual regular market earnings. Partly, this allows us to address the aforementioned shortcoming and capture more information at the extensive margin. Nevertheless, the figure depicts an almost identical result on spousal response to that of the weekly statistics. Evidently, average spousal responses to both negative and positive changes in primary earner's annual earnings are economically insignificant. Though we do see some movement in spouse's earnings, they are inconsistent and do not suggest a conscious counteraction made by the spouse to changes in their partner's income. Perhaps equally striking, though anticipated, is the strong negative correlation between changes in

[26]In appendix D, we show that the observed (lack of) spousal responses holds even more strongly for the permanent and full time subsample.

public transfer and primary earner's income. At the extreme of annual changes for the median income primary earners (top-middle graph in Figure 12), for example, a decrease (*increase*) in their previous annual earnings by -0.8 (0.8) log points corresponds to an increase (*decrease*) of approximately 0.35 (-0.5) log points in public transfer. Response from the transfer system is even greater for richer households in the 9th decile, plausibly owing to the means test on combined family income. The 3-year average change statistics on the bottom panel convey a matching story.

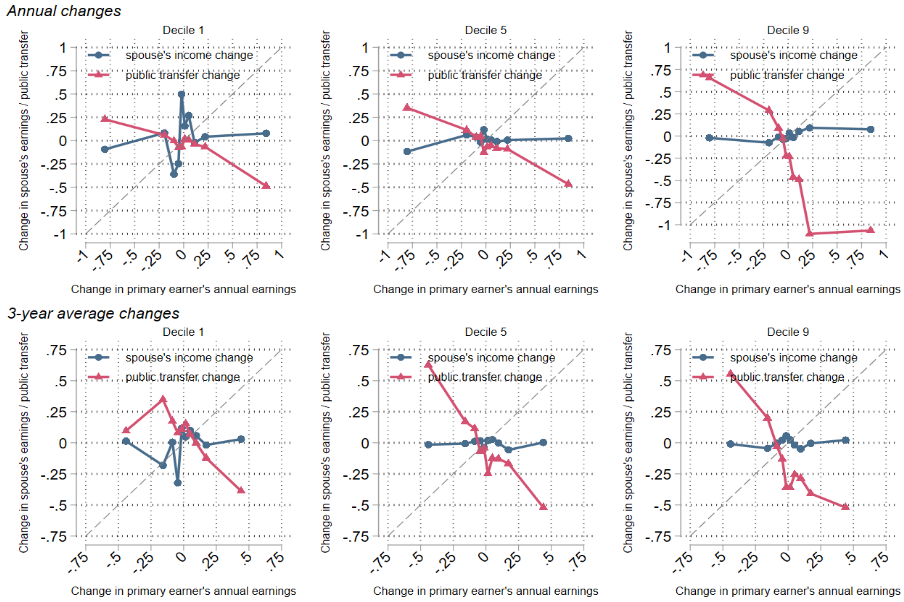

Figure 12: **Changes in spousal earnings and public transfers versus decile of changes in past market earnings of primary earners in the 1st, 5th, and 9th deciles of past regular market income.**

Figures 11 and 12 offer a new perspective and make possible comparison between different directions and degrees of changes. What has become transparent is that, on average, the greatest response to individual earnings changes comes from the public transfer side. The adjustment in spouse earnings tends to be either insignificant or inconsistent. Interestingly, though the sign is weak, it appears that spousal and government responses move in opposite direction. Government insurance may have crowded out family insurance, and how much of the observed spousal behaviour stems from the existence of large public transfer insurance is a subject worth inquiring into.

In summary, section 3.2 demonstrates that the roles of family and government insurance in Australia generally do not overlap. Family market income does not insure against the second-order risk; however, against the higher-order risk, it is a major source of insurance. Conversely, government transfer serves as an effective tool insuring against the second-order risk, especially for young and low income households, but its impact on the third-order risk is comparatively small. Our findings are different from those of De Nardi et al. (2021) which show that government transfers are a major source of insurance in the Netherlands, substantially reducing the standard deviation, negative skewness, and kurtosis of residual income shocks; whereas, the role of family insurance is much larger in the US.[27]

Note that these findings are restricted to employees who constitute the largest share of our sample (84.3%). The sample size of the self-employed is inadequate to get comparable detailed results. A

[27]More precisely, government insurance insures against the second-order earnings risk in the Netherlands, and their joint force with family insurance insures families against the higher-order risk. In the US, government insurance, together with family insurance, have comparable effects in mitigating the second-order risk; however, against the third- and fourth-order risks, family income is the dominant source of insurance.

more specialized data set is necessary. As a preliminary examination, we estimate moment statistics of the self-employed by past income quintile and two broader age groups. Interestingly, we find their family market income and private transfer insurance effects to be non-trivial. See appendix C for further discussion.

4 Extensions

The demographic variability raises questions about the extent to which household structure can affect the role of family and government insurance. In this section we extend our analysis further to consider three key demographics including gender, marital status and parenthood.

4.1 Gender

Households with female primary earners, a.k.a female headed households, account for approximately 39% (46.37% of whom live in partnered households) of our pooled sample of single and partnered employees. We now turn our analysis to male and female subsamples.

Figure 13 compares moment properties of the shock distributions of male (*left panel*) and female (*right panel*) headed households aggregated over age. For both genders, government transfer provides substantial insurance against the dispersion of shocks, particularly for the bottom decile, and relatively small insurance against the negative skewness. Conversely, family market income greatly reduces the negative skewness and kurtosis of shocks, but its dispersion mitigating role is largely absent.

At the same time, there are notable differences. First, the second-order risk of the pre-transfer (post-tax) income of female headed households tends to be larger than those of their male counterparts - especially for the lower three deciles. This is primarily driven by the relatively higher individual earnings shock variance of female heads themselves. A likely secondary cause is the larger share of labour hours and earnings of male secondary earners (in female headed households) as displayed in Table 2.[28] Higher income share of male secondary earners then translates to higher positive influence of shocks to their income on the variance of family income shocks (i.e., income-pooling effect).[29] Having said that, we expect this effect to be small since the gaps between the standard deviations of individual and family market income shock distributions for both male and female are roughly equal in size. Partly due to these individual and household gross earnings dynamics, together with the means-tested and targeted welfare design, government transfer has a stronger insurance effect on the second-order earnings risk of female headed households below the median past market income, whereas only the poorest male headed households benefit from the transfer insurance. Second, concerning the skewness of individual earnings shocks, those of female primary earners are on the whole greater in magnitude. Coupled with the fact that male secondary earners bring home substantially more income than their female counterparts do, this might explain why family market income insurance against the third-order risk is greater for female primary earners. For similar reasons with the second-order risk case, while the government insurance against the third-order risk is small, there is sign of relatively

[28] The substantial fraction of matching between higher income male and lower income female (appendix: Table A.5) might account for the lower earnings of female secondary earners. Note that the lower female secondary earnings is not simply an ex-post marriage adjustment since we also observe educational attainment gap associated with couples (appendix: Table A.6) which is also reflected by the smaller weekly wages of female secondary earners relative to those of male secondary earners as evident in Table 2.

[29] We provide an explicit formula and discussion in the appendix B.2

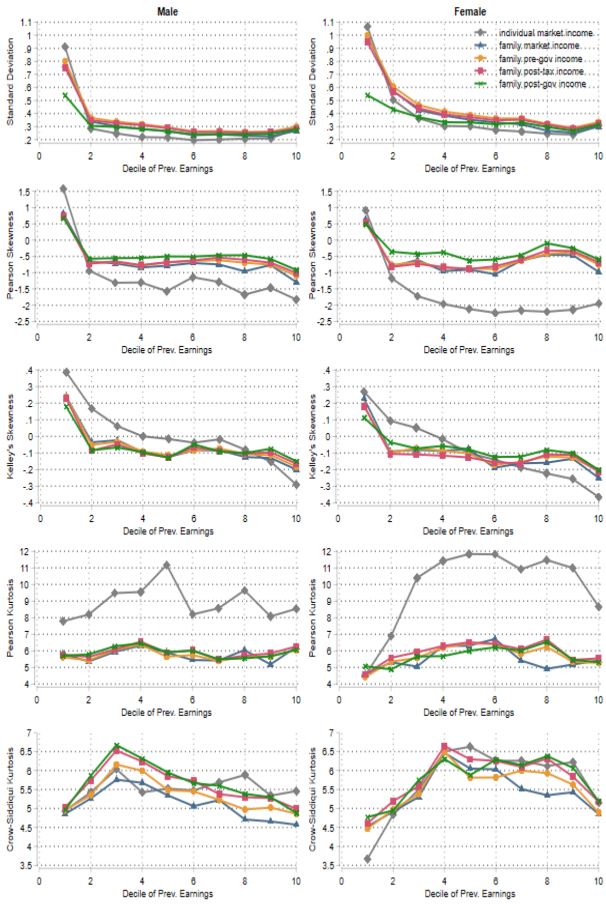

Figure 13: **Second- and higher-order moments of the distributions of annual income shocks of male (left panel) and female (right panel) primary earners and their households (P1-P99 Pearson statistics).**

larger government insurance for female headed households. Regarding the fourth-order risk, family market income appears to be the sole insurance and its effect is in overall larger for female heads.

Secondary Earner		Age	Higher Education	Hours (Weekly)	Wage (Weekly)	Market Income (Annual)	Govt Transfer (Annual)
1	Male	36	47%	29.9	$619.43	$19,554.41	$10,633.30
	Female	34.4	47%	25.3	$566.46	$21,166.45	$11,822.05
2	Male	38.3	57%	35	$823.47	$40,572.98	$5,065.07
	Female	36.3	54%	26.6	$664.96	$29,604.74	$6,705.75
3	Male	40.7	65%	38	$959.69	$49,668.30	$3,046.49
	Female	38.6	58%	29.6	$775.35	$38,089.68	$3,708.15
4	Male	42.3	73%	40	$1,201.26	$65,238.51	$1,729.30
	Female	40	67%	31.9	$958.34	$50,298.72	$1,670.62
5	Male	46.1	82%	41.5	$1,670.71	$104,266.79	$885.92
	Female	42.9	76%	33.9	$1,281.75	$74,134.83	$1,114.50

Table 2: Average 20-year statistics for male and female secondary earners by family market income quintile. All income and transfer values are stated in 2018 Australian dollar.

Male and female primary earners diverge further with respect to persistent income risks. Figure 14 reveals that, at both the individual and household levels, shocks on the female side continue to be more volatile than those on the male side, particularly if they happen to be below the median. Compared to the annual statistics in Figure 13, a marked difference occurs at the bottom-most decile where we see a significant decline in the second-order risk of male primary earners, whereas the improvement, though sizeable in the absolute sense, still leaves the lowest income women worse off than their male and higher income female counterparts. The persistent shock process of female primary earners and their households may be influenced by motherhood and the entailing social security benefits that distort incentive. Institutionally induced rigidities in the labour market can further prevent them from making labour supply adjustment. Precise answers to these questions, however, require a more sophisticated economic model. What is clearly laid out here is that government transfer maintains its status as a crucial source of insurance against the persistent second-order risk for female headed households even when its insurance effect becomes almost trivial for male heads. This has important implications for structural models of households and optimal policies because unlike transitory risks, more persistent adverse risks impact lifetime wealth and are harder to insure through self-insurance mechanisms such as labour supply and savings.

Next, we compare standardized skewness and kurtosis between the two household types. The skewness and kurtosis in Figure 14 exhibit some distinct patterns from those of the annual statistics in Figure 13. On skewness, the distribution of female primary earner's income shocks remains more negatively skewed compared to that of male heads. Family market income insurance still exerts a strong third-order risk mitigating effect for women, particularly for those in the upper past income deciles. Conversely, female heads below the median benefit significantly more from government transfer insurance. For the male group, we see smaller family insurance above the median past income, and little to no government insurance.

On kurtosis, male and female primary earners experience a sharp decrease in their fourth-order risks compared to the corresponding annual statistics. Family market income does reduce kurtosis in this case, but the effect is much less consequential. On the other hand, public and private transfers cause a small increase in kurtosis for both groups. Inspecting their empirical density distributions (figures

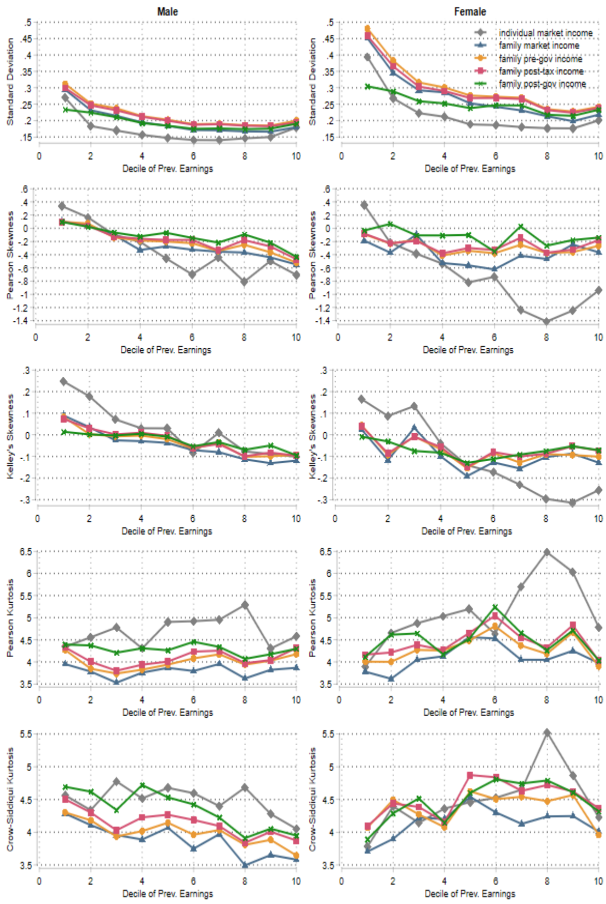

Figure 14: **Second- and higher-order moments of the distributions of 3-year average income shocks of male (left panel) and female (right panel) primary earners (P1-P99 Pearson statistics).**

not included) suggests that the increase in kurtosis stems from higher peakedness of the household disposable income shock distributions as opposed to thicker tails. Transfers may cause changes in their household disposable income to be more clustered about the mean of the shock distribution and thus helps explain the result.

Figures 13 and 14 show significant differences in income dynamics and insurance between male and female headed households. More interestingly, government transfer equalizes the risk outcome between these two household types. An important implication is that examining income level and first moment metrics alone might not allow one to fully grasp the role of family and government insurance across socioeconomic and demographic groups. The supplementary statistics on average government transfer in Table 2, as an example, report a larger average transfer to male headed households even though their female counterpart has been found to persistently benefit more from government insurance against risks. Hence, investigating the second- and higher-order risks are important, though these say nothing about the aggregate efficiency and welfare. Note that, the strength of government insurance effect for female headed households, especially against the third-order risk, weakens when single households (53.63% of the female headed households) are excluded, but the overall pattern remains. Allowing for rich income dynamics and heterogeneities in family structure can therefore improve assessment quality of social insurance effects in quantitative work. De Nardi, Fella and Paz-Pardo (2020) make a similar point using the UK case study.

4.2 Marriage and parenthood

In this subsection, we examine how family and government insurance effects differ among households varied by marital and parental status.[30] Arguably, the weight of parenthood (i.e., child-bearing and child-rearing responsibilities) tends to fall more heavily on mothers and might therefore increase the earnings risk of female headed households. This might explain the persistently greater fluctuations of income shocks and the large government insurance for this group as family support programs are strongly tied to the presence of dependent children.

4.2.1 Parent and non-parent primary earners

The first row of Figure 15 shows the differences between insurance effects against the second-order annual income risks faced by parents (*left panel*) and non-parents (*right panel*). Family market income behaves as a moderate insurance mitigating the individual shock dispersion for parents in the bottom decile but the effect is barely discernible for non-parents. Government transfer insurance is visible for all parents below the median, whereas for non-parents, the insurance is limited to the poorest households. The transfer insurance is at its largest for parents in the bottom decile, more than double that for non-parents.

Figure 16 reports the corresponding 3-year average statistics. It demonstrates the persistence of government insurance for parent households below the median past income even as family insurance has completely vanished. Interestingly, not only does the government transfer insurance effect against the second-order risk for this group remains substantial, it extends to those in the upper brackets. For

[30] We count those legally married or in de facto relationship as married or partnered. Only parents of dependent children are counted as parents. By these definitions, parents account for 39.29% of the 152,884 observations. Partnered primary earners comprise 89.07% of parents and 53.99% of non-parents.

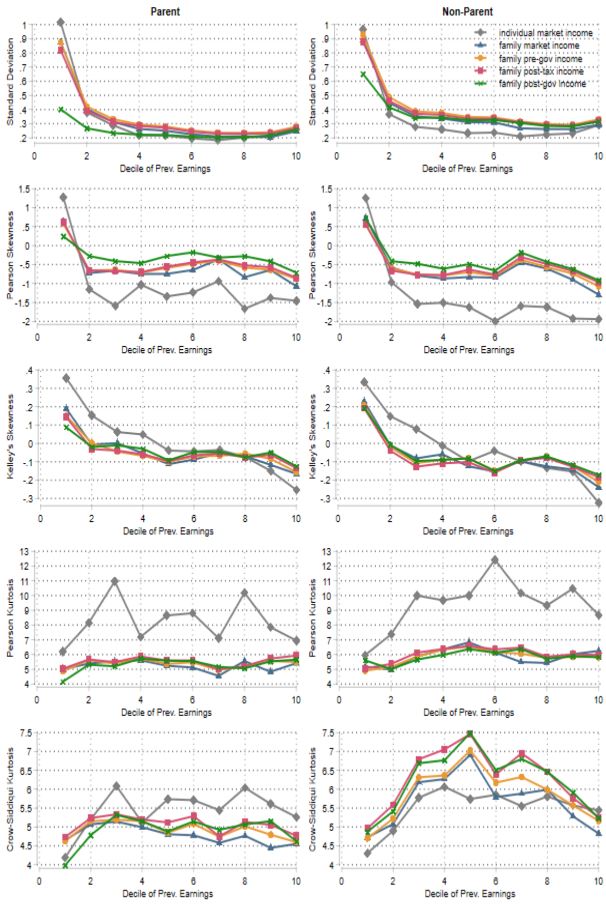

Figure 15: **Second- and higher-order moments of the distributions of annual income shocks of parent (left panel) and non-parent (right panel) primary earners (P1-P99 Pearson statistics).**

non-parents, on the other hand, government transfer continues to serve as a vital source of insurance but only for the lowest decile.

Turning back to Pearson skewness in the second row of Figure 15, we see that family insurance is present for both parents and non-parents, though it is generally larger for latter. To both, the role of government transfer insurance in dampening the transitory third-order risk is small compared to that of family insurance. However, the transfer insurance appears to be more widespread and represents a larger fraction of the total insurance for parent households.[31] This observation matches skewness statistics of the 3-year average changes in Figure 16 which show that for the most part, government insurance for parent households is relatively larger across income status. Additionally, the figure indicates that family market income is still the only primary source of insurance against the third-order risk for non-parents above the median income, whereas for parents within the same past income bracket, their family market income, private transfer, and government transfer make up roughly equal shares of the total insurance.

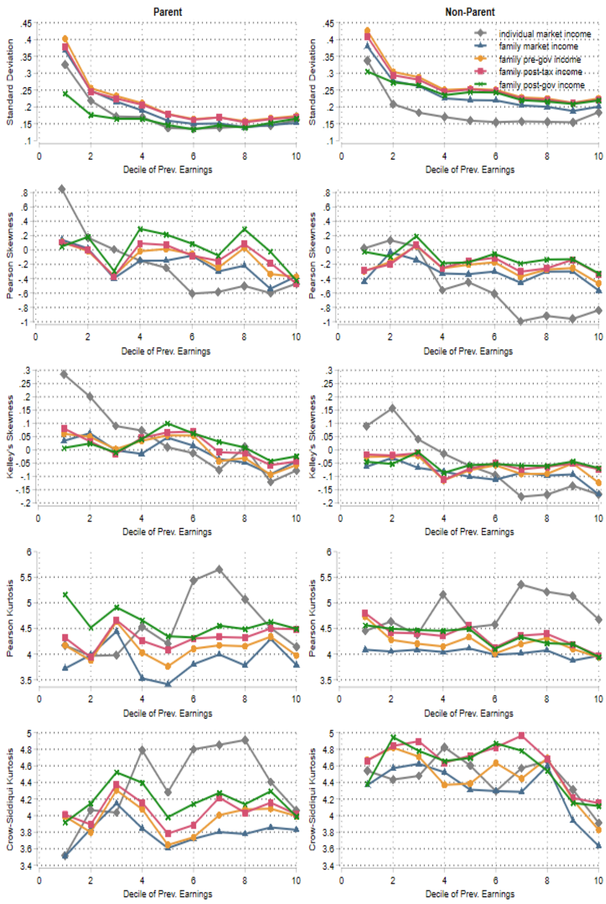

Figure 16: **Second- and higher-order moments of the distributions of 3-year average income shocks of parent (left panel) and non-parent (right panel) primary earners (P1-P99 Pearson statistics).**

The Pearson kurtosis measures in the fourth row of Figures 15 and 16 illustrate that family market income significantly reduces the fourth-order earnings risk for parent and non-parent primary earners alike while government transfer plays virtually no role in the annual statistics and even generates more excess kurtosis in the 3-year average statistics. The question is whether the higher (*lower*) clustering of

[31] The non-robust moment statistics (containing all datapoints at the tails of shock distributions) of Figure F.60 in the appendix show decisively larger government insurance for parents relative to their non-parent counterpart.

shocks around the mean or the increased (*decreased*) density at the tails drives the increase (*decrease*) in the kurtosis level. Further inspection as shown Figures F.48 and F.49 implies that the former scenario is plausible. In other words, government transfer has two counteracting effects on kurtosis: (i) it reduces the tail mass of the shock distribution which lessens kurtosis, and (ii) it creates a larger cluster around the mean, causing the peak of the shock distribution of household disposable income shocks to increase relative to that of the pre-transfer income (transfers counter income shocks) which augments kurtosis. In this instance, the latter process (ii) more than offsets the smaller decline in the tail density (i). Ultimately, the greater peakedness decides the direction of changes in the fourth moment.

We can draw a few critical points from the above discussion. First, the existence of means-tested benefits (independent of labour market participation) targeting parents might help explain the dissimilarities in earnings risk and insurance between parents and non-parents. Second, the results are ex-post statistical measures and do not allow us to infer behavioural responses of households to the incentive (or disincentive) to work and save induced by the transfer system. It is possible that family insurance effect would change substantially were the government insurance absent. Third, in spite of the limitation stated, the inter-group comparison provides a hint of behavioural responses to the presence of government support programs. Suppose that parents have at least as strong an incentive to insure their households against income shocks as non-parents do, then the smaller family market income insurance for parents, despite the large proportion of partnered households within their composition (89.07%), relative to that of non-parents suggests a crowding-out effect of government insurance on family insurance (i.e., work disincentive effect on secondary earners).[32] This would be aligned with our earlier results and the findings by De Nardi et al. (2021) that family insurance effect is stronger in the US than in the Netherlands, the latter of which has a bigger and more pervasive welfare system. The authors point to the potential crowding-out effect of government insurance.

4.2.2 Partnered and lone parents

The prior subsection reveals that parenthood, to a considerable extent, determines the size of government transfer insurance against transitory and persistent income risks in Australia. Provided that the majority of lone parents are female and that female headed households benefit greatly from government insurance, we dedicate this segment to an extended examination along the dimension of marital status.

Figure 17 shows the second- and higher-order moments of the annual income shocks of partnered parent (left) and lone parent households (right). The standard deviation measures in the top row display a stark contrast between insurance effects for the two groups. Lone parents confront a significantly greater second-order risks, measured in terms of pre-government individual and family earnings, than partnered parents within the same bracket do. More interestingly, while family insurance against the second-order risk is missing for lone parents, their government insurance is strikingly large, especially for poorer households. In fact, the insurance magnitude is sufficient to close the initial disparity in pre-fiscal risks between partnered and lone parents such that their household disposable income shock distributions end up at virtually the same level of dispersion. Its effect on partnered parents, on the contrary, is significant only for the bottom decile who appears to benefit equally from family market income and government transfer insurance.

[32] In fact, it is plausible that parents have a stronger incentive to insure their households against shocks.

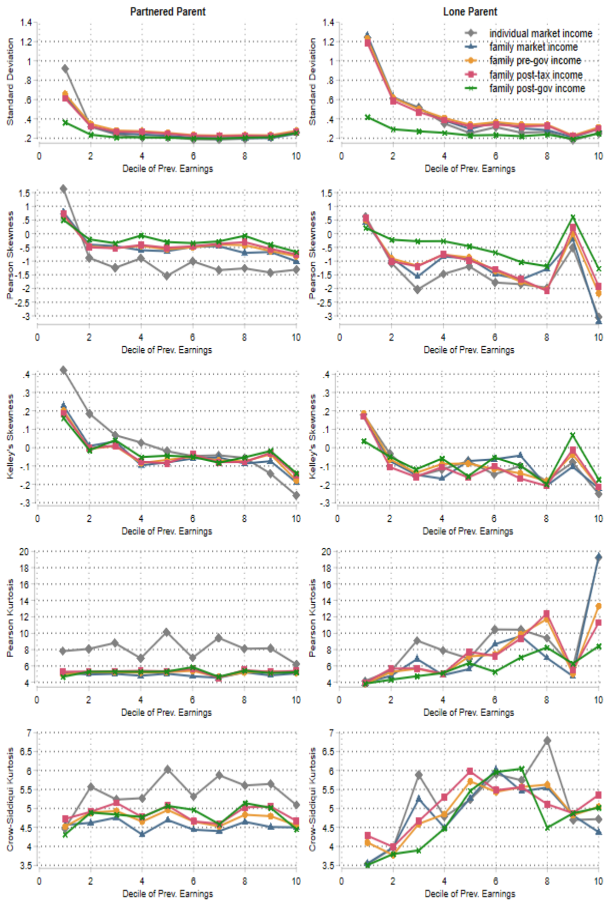

Figure 17: **Second- and higher-order moments of the distributions of annual income shocks of partnered parent (left panel) and lone parent (right panel) primary earners (P1-P99 Pearson statistics).**

Pearson skewness statistics in the second row of Figure 17 yield a similar conclusion. The left panel shows that the dominant insurance against the third-order risk for partnered parents is family market income, while their government insurance is relatively small and intermittent. In contrast, for most lone parent households, a large portion of insurance stems from government transfers. Therefore, in terms of insurance against the third-order risk, the main beneficiary of the government transfer programs is the lone parent households.

Looking at Pearson kurtosis, we observe that government transfers do not lead to any changes in the kurtosis of pre-transfer income shock distribution for partnered parents. While it appears to reduce kurtosis for some lone parent households, the irregular pattern (likely due to the small sample size of lone parents) does not allow us to establish a good baseline for comparison. The more reliable message is that family market income is still the dominant kurtosis mitigating factor. Further examination into the empirical distribution of shocks once again suggests this result is driven by the lower peakedness of the distribution of family market income shocks relative to that of primary earner's market income. Simply speaking, while family market income does reduce the thickness of the tails to a certain degree, it simultaneously introduces a larger probability of moderate shocks.

In overall, our findings indicate that parent households benefit the most from the Australian government transfer programs in terms of their total insurance effect against risks, and the bulk of the benefits goes to lone parents. This in turn equalizes the risk outcomes between partnered and lone parents as manifested by the comparability between their disposable income risks despite the fact that the latter group starts off with much higher dispersion and skewness of pre-transfer income shocks. What is equally intriguing is that the government transfer insurance extends to the upper income lone parents, perhaps a result of the means-tested transfers. Furthermore, because female lone parents constitute the majority of the group, the public transfer insurance should affect them the most. This can deteriorate human capital of the existing and potential female workforce by increasing the proportion of mothers exiting the labour force. However, the insurance also potentially improves the well-being of children and lone mothers themselves. The pros and cons of the transfer programs can be ascertained with quantitative models that capture behavioral responses to such policies and their welfare implication. Using the current work for guidance, this subject is explored in our forthcoming paper.

5 Conclusion

This paper documents evidence of the non-linear and non-Gaussian income dynamics using Australian household survey data, HILDA. Similar to other studies on the OECD countries, earnings risk varies across age and income group. Moreover, the income processes of some specific groups such as the poorest, richest, youngest, and oldest exhibit distinct dynamics.

Our findings also reveal some differences with respect to the roles of wages and hours in explaining income dynamics in Australia. Wage changes drive the second-order earnings risk, whereas hour changes contribute significantly more to the third- and fourth-order risks. In addition, wage changes constitute the main factor explaining the upward and downward movements of earnings changes, while the contribution by hour changes is relatively small. Another interesting finding in this study is related to the roles of family and government insurance against earnings risk. In general, both family market income and government transfer are major sources of insurance against earnings risk. However, government transfer appears to be the dominant mechanism insuring against the second-order risk, whereas family market income insurance is more effective against the third- and fourth-order risks.

Our paper also extends the previous literature on income dynamics by analyzing the importance of demographic characteristics in determining risk and insurance. First, we show that family insurance against the second- and higher-order earnings risks is generally larger for non-parents and government insurance tends to be more pronounced for parents. Along the same line, we highlight the passiveness on the part of spouses and the strong response from public transfers to primary earners earnings shocks. Given the family-oriented nature of the Australian transfer schemes, these could imply a crowding-out effect of government insurance. Second, groups such as female heads and non-parents (not mutually exclusive) experience quite persistent risks that are difficult to self-insure. Third, although the social security system seems to redistribute resources from female to male headed households (who typically represent two-earner and single-earner households, respectively) based on first moment statistics, we show that the former group does benefit substantially from the public transfer insurance when (i) the persistence pre-fiscal earnings risks they face and (ii) the government insurance effect against these risks are taken into account.

For this research we provide a collection of empirical facts on earnings dynamics and insurance. We also provide some conjectures as to what may have generated the observed dynamics of income process. Causality study is beyond the scope of this paper. Moreover, we restrict our sample to primary earners and consequently exclude retirees and the largest transfer program in Australia, the Age Pension. Accounting for the Age Pension may enlarge the role of government insurance. We currently condition the moment statistics on past income. Conditioning on wealth can further enrich our understanding. Furthermore, we abstract from consumption risk. An analysis of consumption contains crucial economic elements pertaining to family and government, namely, consumption equivalence scale, non-cash transfers, and indirect taxes, among others. We leave these issues for future research.

References

Arellano, Manuel, Richard Blundell and Stephane Bonhomme. 2017. "Earnings and Consumption Dynamics: A nonlinear panel data framework." *Econometrica* 85(3):693–734.

Chatterjee, A., A. Singh and T. Stone. 2016. "Understanding Wage Inequality in Australia." *Economic Record* 92:348–60.

De Nardi, Mariacristina, Giulio Fella and Gonzalo Paz-Pardo. 2020. "Wage Risk and Government and Spousal Insurance." *NBER Working Paper* .

De Nardi, Mariacristina, Giulio Fella, Marike Knoef, Gonzalo Paz-Pardo and Raun Van Ooijen. 2021. "Family and Government Insurance: Wage, Earnings, and Income Risks in the Netherlands and the US." *Journal of Public Economics* 193:104327.
URL: *http://www.sciencedirect.com/science/article/pii/S0047272720301912*

Freestone, Owen. 2018. "The Drivers of Life-Cycle Wage Inequality in Australia." *Economic Record* 97 (307):424–444.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan and Jae Song. 2021. "What Do Data on Millions of US Workers Reveal about Life-Cycle Earning Risk?" *Econometrica* 89(5)(20913):2303–2339.
URL: *http://www.nber.org/papers/w20913*

Halvorsen, Elin, Hans Holter, Serdar Ozkan and Kjetil Storesletten. 2020. "Dissecting Idiosyncratic Earnings Risk." *Working Paper* (15395).
URL: *https://ideas.repec.org/p/cpr/ceprdp/15395.html*

Herault, Nicolas and Francisco Azpitarte. 2015. "Recent trends in income redistribution in Australia: Can changes in the tax-benefit system account for the decline in redistribution?" *Economic Record* 91(292):38–53.

Huckfeldt, Christopher. 2018. Understanding the Scarring Effect of Recessions. 2018 Meeting Papers 1207 Society for Economic Dynamics.
URL: *https://ideas.repec.org/p/red/sed018/1207.html*

Kaplan, Greg, Gianni La Cava and Tahlee Stone. 2018. "Household Economic Inequality in Australia." *Economic Record* 94:117–134.

Kaygusuz, Remzi. 2015. "Social Security and Two-earner Households." *Journal of Economic Dynamics and Control* 59:163–178.
URL: *http://www.sciencedirect.com/science/article/pii/S0165188915001360*

Lise, Jeremy. 2012. "On-the-Job Search and Precautionary Savings." *The Review of Economic Studies* 80(3):1086–1113.
URL: *https://doi.org/10.1093/restud/rds042*

Nishiyama, Shinichi. 2019. "The joint labor supply decision of married couples and the U.S. Social Security pension system." *Review of Economic Dynamics* 31:277–304.
URL: *https://www.sciencedirect.com/science/article/pii/S1094202518302424*

Tran, Chung and Nabeeh Zakariyya. 2021. “Tax Progressivity in Australia: Facts, Measurements and Estimates.” *Economic Record* 97 (316):45–77.

Appendices

A HILDA: Descriptive statistics

Financial year	Individual	Household	Family (excl. lone person)	Family (incl. lone person)
2000-01	6,360	4,396	3,495	4,531
2001-02	6,143	4,296	3,363	4,404
2002-03	6,103	4,257	3,305	4,358
2003-04	5,955	4,167	3,192	4,255
2004-05	6,277	4,334	3,307	4,446
2005-06	6,415	4,425	3,376	4,555
2006-07	6,461	4,434	3,396	4,530
2007-08	6,542	4,474	3,406	4,574
2008-09	6,641	4,543	3,508	4,656
2009-10	6,787	4,605	3,572	4,724
2010-11	8,768	6,012	4,717	6,186
2011-12	8,688	5,956	4,661	6,105
2012-13	8,613	5,926	4,628	6,079
2013-14	8,703	5,966	4,659	6,122
2014-15	8,748	5,992	4,748	6,127
2015-16	8,748	6,016	4,739	6,137
2016-17	8,839	6,018	4,741	6,147
2017-18	8,915	6,044	4,776	6,180
2018-19	8,885	6,031	4,762	6,162
2019-20	8,405	5,794	4,621	5,898
Total	150,996	103,686	80,972	106,176

Table A.1: Sample size by year and unit of observation. The sample excludes employer/self-employed, unpaid family worker, dependent children and students, retirees, non-working students, and those with full-time domestic duties. For partnered individuals, if their partner falls into one of these categories, his/her data on income, tax, transfer and other variables of interest is stored prior to being dropped.

Table A.2: Summary statistics of primary earners in financial year 2001

Primary Earner		N	Mean	Median	SD	Min	Max
Age	Individual	3,872	40.82	40	9.73	25	64
	Family	3,872	-	-	-	-	-
Weekly hours	Individual	3,872	40.09	40	13.09	0	120
	Family	3,872	53.01	47	32.39	0	201
Weekly wage	Individual	3,872	1,292.20	1,144.11	833.72	0.00	14,189.97
	Family	3,872	1,854.35	1,629.21	1,195.40	0.00	14,189.97
Labour Income	Individual	3,872	66,296.91	59,623.97	47,176.12	0.00	915,285.31
	Family	3,872	96,419.84	84,933.90	65,805.50	0.00	915,285.31
Market income	Individual	3,872	68,764.74	61,171.57	48,541.73	-53,391.64	916,353.19
	Family	3,872	103,635.25	91,527.77	73,219.05	-28,221.30	1.51e+06
Private transfer	Individual	3,872	414.57	0.00	2,450.85	0.00	36,611.41
	Family	3,872	605.10	0.00	3,016.12	0.00	44,543.89
Total income tax	Individual	3,872	16,818.29	12,684.33	18,900.91	-3,252.31	391,345.50
	Family	3,872	23,958.07	17,950.27	26,017.05	-8,808.10	637,691.50
Public transfer	Individual	3,872	2,366.43	0.00	5,257.32	0.00	47,440.77
	Family	3,872	5,276.89	0.00	8,855.15	0.00	69,825.59

	Age 25-34		Age 35-44		Age 45-54		Age 55-64		
Past decile	Part-time	Full-time	Part-time	Full-time	Part-time	Full-time	Part-time	Full-time	Total
1	188	231	418	247	389	276	320	143	2,212
	53.56%	6.90%	48.21%	3.64%	44.20%	3.81%	45.58%	4.40%	9.44%
	8.50%	10.44%	18.90%	11.17%	17.59%	12.48%	14.47%	6.46%	100.00%
2	51	419	177	593	137	604	96	268	2,345
	14.53%	12.51%	20.42%	8.73%	15.57%	8.34%	13.68%	8.24%	10.01%
	2.17%	17.87%	7.55%	25.29%	5.84%	25.76%	4.09%	11.43%	100.00%
3	35	450	54	630	78	684	77	340	2,348
	9.97%	13.43%	6.23%	9.28%	8.86%	9.44%	10.97%	10.45%	10.02%
	1.49%	19.17%	2.30%	26.83%	3.32%	29.13%	3.28%	14.48%	100.00%
4	27	407	58	681	80	708	55	332	2,348
	7.69%	12.15%	6.69%	10.03%	9.09%	9.77%	7.83%	10.21%	10.02%
	1.15%	17.33%	2.47%	29.00%	3.41%	30.15%	2.34%	14.14%	100.00%
5	15	445	41	753	66	708	46	298	2,372
	4.27%	13.28%	4.73%	11.09%	7.50%	9.77%	6.55%	9.16%	10.12%
	0.63%	18.76%	1.73%	31.75%	2.78%	29.85%	1.94%	12.56%	100.00%
6	14	324	36	847	38	783	42	268	2,352
	3.99%	9.67%	4.15%	12.47%	4.32%	10.81%	5.98%	8.24%	10.03%
	0.60%	13.78%	1.53%	36.01%	1.62%	33.29%	1.79%	11.39%	100.00%
7	13	311	35	771	39	842	19	343	2,373
	3.70%	9.28%	4.04%	11.35%	4.43%	11.62%	2.71%	10.54%	10.12%
	0.55%	13.11%	1.47%	32.49%	1.64%	35.48%	0.80%	14.45%	100.00%
8	5	292	26	724	22	886	15	389	2,359
	1.42%	8.72%	3.00%	10.66%	2.50%	12.23%	2.14%	11.96%	10.06%
	0.21%	12.38%	1.10%	30.69%	0.93%	37.56%	0.64%	16.49%	100.00%
9	3	252	11	749	28	897	18	408	2,366
	0.85%	7.52%	1.27%	11.03%	3.18%	12.38%	2.56%	12.54%	10.09%
	0.13%	10.65%	0.46%	31.66%	1.18%	37.91%	0.76%	17.24%	100.00%
10	0	219	11	795	3	857	14	464	2,363
	0.00%	6.54%	1.27%	11.71%	0.34%	11.83%	1.99%	14.26%	10.08%
	0.00%	9.27%	0.47%	33.64%	0.13%	36.27%	0.59%	19.64%	100.00%
Total	351	3,350	867	6,790	880	7,245	702	3,253	23,438
	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	1.50%	14.29%	3.70%	28.97%	3.75%	30.91%	3.00%	13.88%	100.00%

Table A.3: Proportion of primary earners in part-time employment by decile of usual weekly wages from main job. The subsample contains primary earners who report positive usual weekly labour earnings for at least 18 years of observation.

	Age 25-34		Age 35-44		Age 45-54		Age 55-64		
Past decile	Casual	Permanent	Casual	Permanent	Casual	Permanent	Casual	Permanent	Total
1	113	306	130	535	135	532	116	347	2,214
	31.92%	9.15%	30.23%	7.40%	33.33%	6.89%	37.54%	9.52%	9.45%
	5.10%	13.82%	5.87%	24.16%	6.10%	24.03%	5.24%	15.67%	100.00%
2	51	419	58	713	64	677	51	313	2,346
	14.41%	12.52%	13.49%	9.86%	15.80%	8.77%	16.50%	8.58%	10.01%
	2.17%	17.86%	2.47%	30.39%	2.73%	28.86%	2.17%	13.34%	100.00%
3	52	433	51	633	47	715	36	381	2,348
	14.69%	12.94%	11.86%	8.76%	11.60%	9.26%	11.65%	10.45%	10.02%
	2.21%	18.44%	2.17%	26.96%	2.00%	30.45%	1.53%	16.23%	100.00%
4	26	408	35	705	38	750	20	367	2,349
	7.34%	12.19%	8.14%	9.75%	9.38%	9.71%	6.47%	10.07%	10.02%
	1.11%	17.37%	1.49%	30.01%	1.62%	31.93%	0.85%	15.62%	100.00%
5	23	437	23	770	24	750	14	330	2,371
	6.50%	13.06%	5.35%	10.65%	5.93%	9.71%	4.53%	9.05%	10.12%
	0.97%	18.43%	0.97%	32.48%	1.01%	31.63%	0.59%	13.92%	100.00%
6	15	323	26	857	16	805	14	296	2,352
	4.24%	9.65%	6.05%	11.86%	3.95%	10.42%	4.53%	8.12%	10.03%
	0.64%	13.73%	1.11%	36.44%	0.68%	34.23%	0.60%	12.59%	100.00%
7	15	309	16	790	16	865	17	345	2,373
	4.24%	9.23%	3.72%	10.93%	3.95%	11.20%	5.50%	9.46%	10.12%
	0.63%	13.02%	0.67%	33.29%	0.67%	36.45%	0.72%	14.54%	100.00%
8	15	282	21	729	15	893	7	397	2,359
	4.24%	8.43%	4.88%	10.09%	3.70%	11.56%	2.27%	10.89%	10.06%
	0.64%	11.95%	0.89%	30.90%	0.64%	37.86%	0.30%	16.83%	100.00%
9	26	228	19	741	20	905	9	417	2,365
	7.34%	6.81%	4.42%	10.25%	4.94%	11.72%	2.91%	11.44%	10.09%
	1.10%	9.64%	0.80%	31.33%	0.85%	38.27%	0.38%	17.63%	100.00%
10	18	201	51	755	30	830	25	453	2,363
	5.08%	6.01%	11.86%	10.45%	7.41%	10.75%	8.09%	12.42%	10.08%
	0.76%	8.51%	2.16%	31.95%	1.27%	35.12%	1.06%	19.17%	100.00%
Total	354	3,346	430	7,228	405	7,722	309	3,646	23,440
	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	1.51%	14.27%	1.83%	30.84%	1.73%	32.94%	1.32%	15.55%	100.00%

Table A.4: Proportion of primary earners in casual employment by decile of usual weekly wages from main job. The subsample contains primary earners who report positive usual weekly labour earnings for at least 18 years of observation.

		Married		Single		
Income Quintile	Parenthood	Male	Female	Male	Female	Total
Q1	Non-parent	143	455	238	177	1,013
		4.34%	12.14%	21.38%	19.39%	11.17%
		14.12%	44.92%	23.49%	17.47%	100.00%
	Parent	167	809	12	117	1,105
		5.07%	21.58%	1.08%	12.81%	12.18%
		15.11%	73.21%	1.09%	10.59%	100.00%
Q2	Non-parent	200	407	319	217	1,143
		6.07%	10.86%	28.66%	23.77%	12.60%
		17.50%	35.61%	27.91%	18.99%	100.00%
	Parent	234	597	1	32	864
		7.10%	15.93%	0.09%	3.50%	9.53%
		27.08%	69.10%	0.12%	3.70%	100.00%
Q3	Non-parent	327	379	261	179	1,146
		9.92%	10.11%	23.45%	19.61%	12.64%
		28.53%	33.07%	22.77%	15.62%	100.00%
	Parent	399	386	2	19	806
		12.11%	10.30%	0.18%	2.08%	8.89%
		49.50%	47.89%	0.25%	2.36%	100.00%
Q4	Non-parent	361	255	165	120	901
		10.95%	6.80%	14.82%	13.14%	9.93%
		40.07%	28.30%	18.31%	13.32%	100.00%
	Parent	548	219	2	1	770
		16.63%	5.84%	0.18%	0.11%	8.49%
		71.17%	28.44%	0.26%	0.13%	100.00%
Q5	Non-parent	349	129	111	51	640
		10.59%	3.44%	9.97%	5.59%	7.06%
		54.53%	20.16%	17.34%	7.97%	100.00%
	Parent	568	112	2	0	682
		17.23%	2.99%	0.18%	0.00%	7.52%
		83.28%	16.42%	0.29%	0.00%	100.00%
	Total	3,296	3,748	1,113	913	9,070
	%	100.00%	100.00%	100.00%	100.00%	100.00%
	%	36.34%	41.32%	12.27%	10.07%	100.00%

Table A.5: Cross-tabulation of frequencies between parenthood, marital status, and gender. Since HILDA tracks individuals and their households over time, we present a snapshot of the first cohort entering the survey in 2001. The table suggests a negative assortative matching (or matching of unlike) between higher income males and lower income females.

	Married		Single		
Highest education attained	Male	Female	Male	Female	Total
High school or lower	1,226	2,227	639	494	4,586
	37.20%	59.45%	57.41%	54.11%	50.57%
	26.73%	48.56%	13.93%	10.77%	100.00%
Above high school,	1,741	1,221	424	350	3,736
at most bachelor's degree	52.82%	32.59%	38.10%	38.34%	41.20%
	46.60%	32.68%	11.35%	9.37%	100.00%
Above bachelor's degree,	329	298	50	69	746
at most post-graduate degree	9.98%	7.96%	4.49%	7.56%	8.23%
	44.10%	39.95%	6.70%	9.25%	100.00%
Total	3,296	3,746	1,113	913	9,068
%	100.00%	100.00%	100.00%	100.00%	100.00%
%	36.35%	41.31%	12.27%	10.07%	100.00%

Table A.6: Cross-tabulation of frequency between education, marital status, and gender. Since HILDA tracks individuals and their households over time, we present a snapshot of the first cohort entering the survey in 2001. The table suggests a negative assortative matching (or matching of unlike) between higher education males and lower education females. The observed pattern becomes less pronounced in later years of the survey, partly due to attrition and the inclusion of new and younger households.

Income Decile	N	Individual Labour Income	Individual Market Income	Household Pre-gov't Income	Household Disposable Income
1	10,965	58.64%	56.27%	29.11%	16.23%
2	10,964	5.86%	5.97%	4.17%	0.22%
3	10,950	-0.88%	-0.24%	2.54%	-0.01%
4	10,940	-3.20%	-3.20%	-0.56%	-1.42%
5	10,982	-4.45%	-4.03%	-1.73%	1.00%
6	10,930	-4.86%	-4.82%	-2.49%	-1.85%
7	10,950	-4.51%	-4.79%	-2.31%	-1.90%
8	10,947	-4.17%	-4.84%	-3.95%	-1.89%
9	10,953	-5.39%	-6.17%	-3.60%	-2.82%
10	10,948	-7.80%	-10.00%	-7.16%	-5.83%

Table A.7: Average Annual Residual Income Growth (2001-2020) of Employees. The growth statistics shown are for employees (not self-employed) age 25-64. The residual changes are obtained from controlling for time and age effects (see equation 1). The figures account for cross-decile mobility over time.

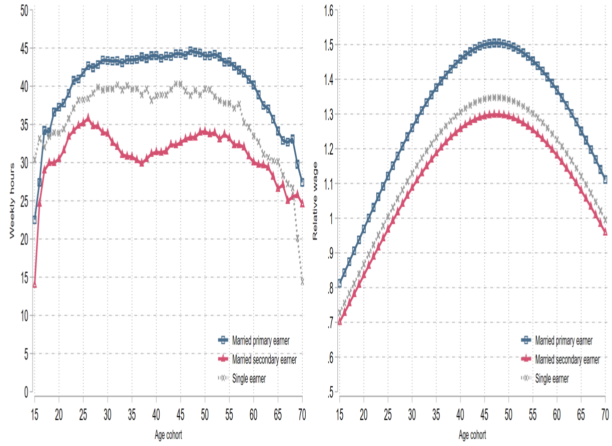

Figure A.1: **Age profiles of weekly work hours and wages**.

Notes: Figure A.1 reports the hump-shaped age profiles of hours and wages. Wages are normalised to male wage in age 21.

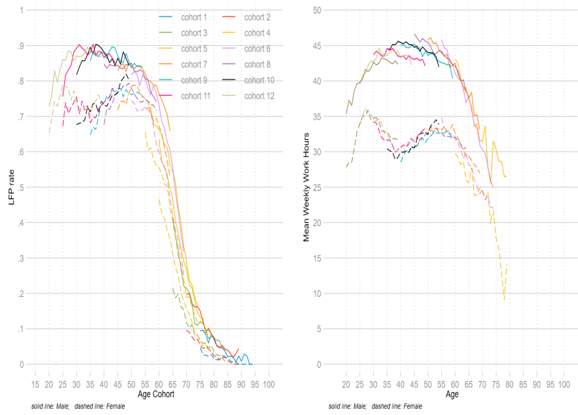

Figure A.2: Age-profile of weekly work hours if employed (left panel) and labour force participation rate (right panel) by age, cohort and gender (2001-2020). The M shape of female labour supply reflects the age-profiles of participation rate and work hour of partnered women. Single women's profiles are hump-shaped, though at a slightly lower level compared to men's.

B Derivations

B.1 Higher-order moments

Let y,w, and h denote earnings, wages, and hours of work, respectively. For each individual i at time t, we have $y_{i,t} = w_{i,t} \times h_{i,t}$, which can be transformed into an equation of changes per unit time. Suppressing the subscripts, the equation can be written as $\Delta y = \Delta w + \Delta h$. Let $\tilde{\mu}_z^k := \mathbb{E}\left(\frac{z-\mu_z}{\sigma_z}\right)^k$ be the k^{th} standardized moment of a random variable z, where $\mu_z := \mathbb{E}(z)$, and $\sigma_z := \sqrt{var(z)} = \sqrt{\mathbb{E}(z-\mu_z)^2}$. We then derive and decompose the second, third, and fourth moments of earning changes, Δy.

Second Moment

$$
\begin{aligned}
var(\Delta y) &= var(\Delta w + \Delta h) \\
&= var(\Delta w) + var(\Delta h) + 2cov(\Delta w, \Delta h)
\end{aligned}
$$

Or, equivalently

$$
\sigma_{\Delta y}^2 = \sigma_{\Delta w}^2 + \sigma_{\Delta h}^2 - 2cov(\Delta w, \Delta h)
$$

Third Moment

Following the definition of the standardized third moment,

$$
\begin{aligned}
\tilde{\mu}_{\Delta y}^3 &= \mathbb{E}\left(\frac{\Delta y - \mu_{\Delta y}}{\sigma_{\Delta y}}\right)^3 \\
&= \frac{1}{\sigma_{\Delta y}^3}\mathbb{E}\left[\Delta y^3 - 3\Delta y^2 \mu_{\Delta y} + 3\Delta y \mu_{\Delta y}^2 - \mu_{\Delta y}^3\right] \\
&= \frac{1}{\sigma_{\Delta y}^3}\left[\mathbb{E}(\Delta w - \mu_{\Delta w})^3 + \mathbb{E}(\Delta h - \mu_{\Delta h})^3\right] \\
&\quad + \frac{3}{\sigma_{\Delta y}^3}\mathbb{E}\left[(\Delta h - \mu_{\Delta h})^2(\Delta w - \mu_{\Delta w})\right] \\
&= \frac{1}{\sigma_{\Delta y}^3}\left[\sigma_{\Delta w}^3\tilde{\mu}_{\Delta w}^3 + \sigma_{\Delta h}^3\tilde{\mu}_{\Delta h}^3\right] \\
&\quad + \frac{3}{\sigma_{\Delta y}^3}\left[\mathbb{E}(\Delta h - \mu_{\Delta h})^2(\Delta w - \mu_{\Delta w}) + \mathbb{E}(\Delta w - \mu_{\Delta w})^2(\Delta h - \mu_{\Delta h})\right],
\end{aligned}
$$

where the first term of the RHS denotes the contributions of Δw and Δh independently to the Pearson skewness of Δy, and the second term of the RHS denotes the contribution of the co-movement of Δw and Δh to the Pearson skewness of Δy.

Fourth Moment

We follow a similar procedure to derive the below expression of the standardized fourth moment (Pearson kurtosis) of income changes:

$$
\begin{aligned}
\tilde{\mu}^4_{\Delta y} &= \mathbb{E}\left(\frac{\Delta y - \mu_{\Delta y}}{\sigma_{\Delta y}}\right)^4 \\
&= \frac{1}{\sigma^4_{\Delta y}}\left[\mathbb{E}(\Delta w - \mu_{\Delta w})^4 + \mathbb{E}(\Delta h - \mu_{\Delta h})^4\right] \\
&\qquad + \frac{4}{\sigma^4_{\Delta y}}\mathbb{E}\left[(\Delta h - \mu_{\Delta h})^3(\Delta w - \mu_{\Delta w})\right] + \frac{4}{\sigma^4_{\Delta y}}\mathbb{E}\left[(\Delta w - \mu_{\Delta w})^3(\Delta h - \mu_{\Delta h})\right] \\
&\quad + \frac{6}{\sigma^4_{\Delta y}}\mathbb{E}\left[(\Delta w - \mu_{\Delta w})^2(\Delta h - \mu_{\Delta h})^2\right] \\
&= \frac{1}{\sigma^4_{\Delta y}}\left[\sigma^4_{\Delta w}\tilde{\mu}^4_{\Delta w} + \sigma^4_{\Delta h}\tilde{\mu}^4_{\Delta h}\right] \\
&\qquad + \frac{4}{\sigma^4_{\Delta y}}\mathbb{E}\left[(\Delta h - \mu_{\Delta h})^3(\Delta w - \mu_{\Delta w}) + (\Delta w - \mu_{\Delta w})^3(\Delta h - \mu_{\Delta h})\right] \\
&\quad + \frac{6}{\sigma^4_{\Delta y}}\mathbb{E}\left[(\Delta w - \mu_{\Delta w})^2(\Delta h - \mu_{\Delta h})^2\right].
\end{aligned}
$$

As in the previous case, the first term of the RHS denotes the contributions of Δw and Δh independently to the Pearson kurtosis of Δy, and the second and third terms of the RHS denote the contribution of the co-movement of Δw and Δh to the Pearson kurtosis of Δy.

B.2 Income pooling and added worker effects

Let $f, p,$ and s denote family income, primary earner's earnings and secondary earner's earnings,respectively. Family income is a sum of primary earner's and secondary earner's earnings $f(p(t), s(t)) = p(t) + s(t)$. By total differentiation,

$$
\begin{aligned}
\frac{df}{dt} &= \frac{\partial f}{\partial p}\frac{dp}{dt} + \frac{\partial f}{\partial s}\frac{ds}{dt} \\
df &= dp + ds \\
\frac{df}{f} &= \frac{p}{f}\frac{dp}{p} + \frac{s}{f}\frac{ds}{s}
\end{aligned}
$$

Equivalently, $\%\Delta f = f_p \times \%\Delta p + f_s \times \%\Delta s$, where $f_p$denotes the family income share of the primary earner's earnings and f_s denotes the family income share of the secondary earner's earnings such that $f_p + f_s = 1$. Note that $f_p > f_s$ by our definition of primary earner, which implies $f_s \in [0, 0.5)$. The expression of the variance of family income changes (or, the second-order family income risk) is then

$$
VAR(\Delta f) = f_p^2 VAR(\Delta p) + \overbrace{f_s^2 VAR(\Delta s)}^{\text{income-pooling effect}} + \overbrace{2 f_p f_s COV(\Delta p, \Delta s)}^{\text{added-worker effect}}.
$$

The first term $f_p^2 VAR(\Delta p)$ denotes the contribution of primary earner's earnings shock variance to the second-order risk of family income. The second term $f_s^2 VAR(\Delta s)$ denotes the contribution of secondary earner's shock variance, known as the *income-pooling effect*, which enlarges the variance of family income. The last term $2f_pf_sCOV(\Delta p, \Delta s)$ is the contribution of the covariance. $COV(\Delta p, \Delta s) < 0$ implies the *added-worker effect* which contracts the variance of family income. Adding more second earners (e.g., resident independent children) reduces f_p and may lead to a larger influence of $VAR(\Delta s)$.

C Income risk and insurance for the self-employed

Our primary objective is examining the moment statistics of employees (i.e., non-family workers in non-own businesses) to obtain risk and insurance estimates comparable to those from the previous studies. For this reason and for the lack of sufficient sample size (see subsection 2.1), the income dynamics of the self-employed - including employees of family run businesses - is excluded from the main study. Some other challenges involve the fact that family members working in family-own businesses might be unpaid or report an identical income level (joint income is evenly split), and that the self-employed makes up a trivial fraction of certain demographics of interest (e.g., bottom income decile and/or single mothers). As a supplementary study to provide a more complete picture, we conduct two investigations as follows.

We first include the self-employed into our existing sample of employees. This raises the number of observations to $179,674$, a 15.77% increase. To address the issue of self-employed couples reporting identical annual market income, we re-define a primary earner as either the person with higher income relative to their partner for at least half the period of observation, or in case of identical income levels, we assign male as the primary earner to be consistent with the previous work on male income dynamics. We then re-estimate all the second- and higher-order moments in the main paper. We find no significant difference. This suggests that our results are robust to the inclusion of the self-employed sample from HILDA.

Given the relatively small sample size of the self-employed, the finding above is not surprising. Hence, in the second investigation, we study this group in isolation. To accommodate the smaller sample of $26,771$ observations, estimates are re-calculated at a lower resolution by dividing them into income quintile and young/old as opposed to the more finely segmented subgroups done for employees (e.g., income decile and 4 age cohorts).

The effort leads to some interesting findings. The risk and insurance experienced by the self-employed and by employees from the main study exhibit a lot of similarities. For instance, while the sizes of total insurance are similar, the share of government insurance against the second- and third-order risks is larger for the female self-employed primary earners (relative to their male counterparts). Transitory and persistent individual market income risk profiles of self-employed parents resemble those of non-parents, but the former group benefits substantially more from government insurance. The comparison between partnered and lone self-employed parents yields similar results as discussed in the main paper for the employees. The key difference between the employees and the self-employed primary earners can be summarized in few figures.

Figure C.1 shows that though government transfers still is the dominant insurance against the second-order risk for the self-employed primary earners, their family market income insurance is quite substantial. Notably, however, because both partner's business earnings tend to move in the same direction (for joint ownership), Figure C.2 below shows that the average changes in spouse's regular earnings tend to move in the same direction as that of the primary earner. Government transfer is the one to respond to changes in primary earner's earnings. However, the second moment statistics show evidence of insurance by spouse against the second-order risk, not captured by the simpler average change statistics. There are two lessons here. First, the study of average changes alone might therefore miss the family insurance. Second, the observed family market income insurance implies that shocks to earnings of the self-employed heads of households induce secondary earners - who previously jointly owned or were employed by the family business - to search for employment elsewhere in the labour

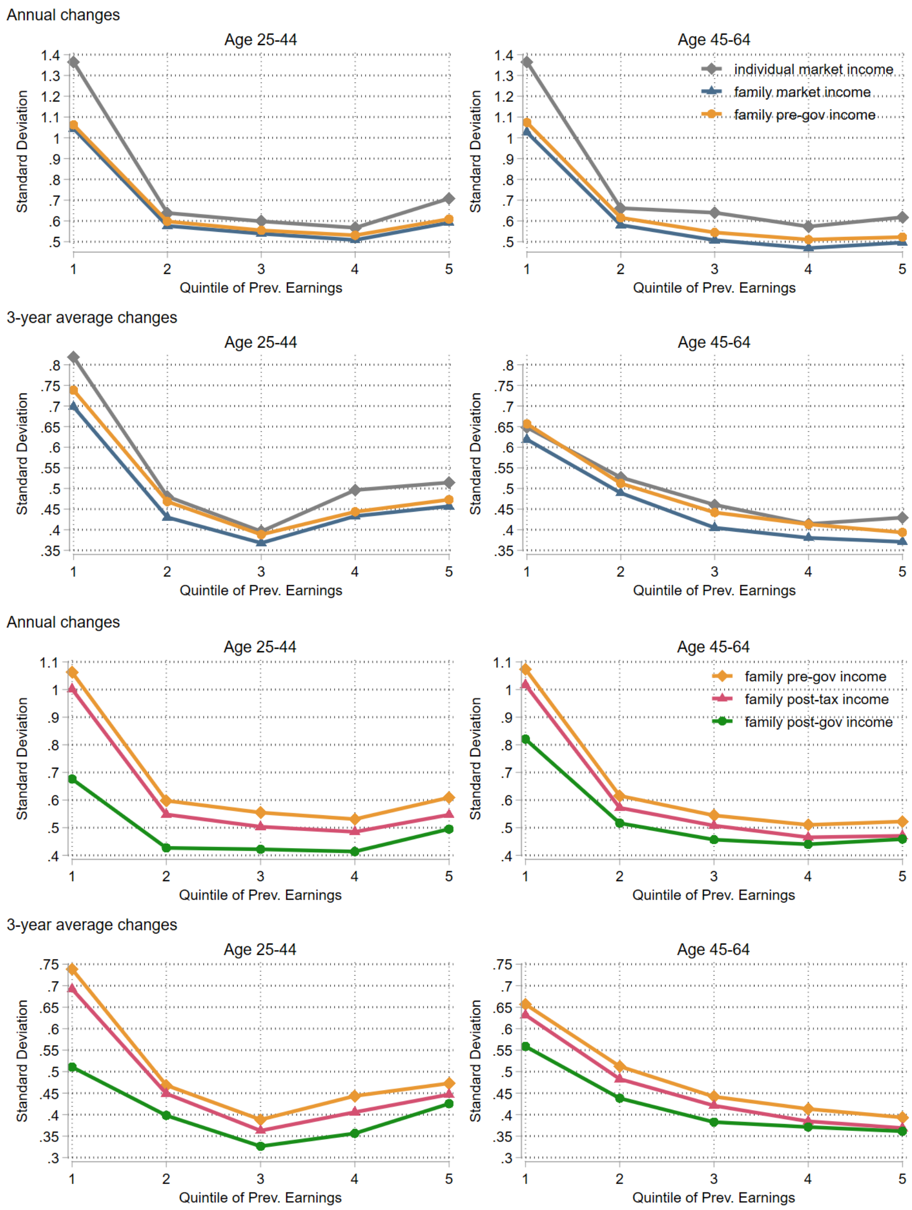

Figure C.1: Family insurance (top panel) and government insurance (bottom panel) against second-order risk for the self-employed market.

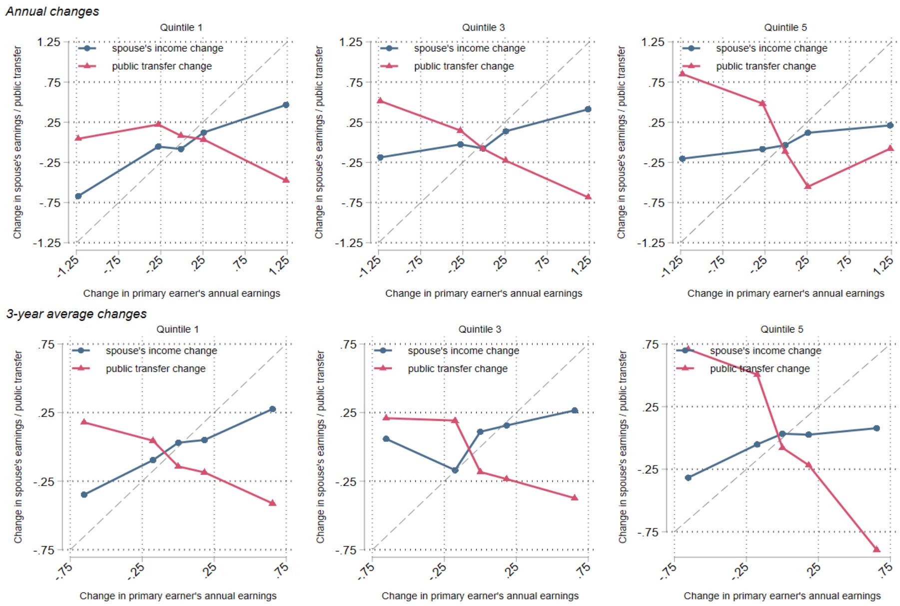

Figure C.2: Spousal versus Government responses to earnings shocks of the self-employed grouped by selected quintiles (Q1, Q3 and Q5).

D Earnings, hour and wage dynamics for permanent and full-time employees

Both the top and bottom panels of figure D.1 support our suspicion that the presence of casual and part time employment (not mutually exclusive) is key to understanding the role that hour changes play in driving the second- and high-order earnings risks, especially for the bottom income decile. Removing casual and part time results in hours having a much weaker influence on the earnings risk. For the second moment statistics, the income profiles of earnings risks drops in level across the board, and wage changes become the sole driver of the earnings dynamics. What is striking is that the latter statement holds even more strongly for the permanent and full-time primary earners in the bottom-most past income decile.

For the third- and fourth-order risks, although wage changes now explain a higher proportion of the dynamics of this restricted sample, the magnitude of transitory earnings risk does not diminish. The relative third-order risk between income groups also remains mostly intact. For instance, permanent and full-time employees in the upper bracket still undergo higher third- and fourth-order earnings risks compared to the rest of the group. However, we now see the bottom decile permanent and full-time workers experiencing much higher extreme magnitude and probability of positive earnings shocks driven primarily by residual wage growth.

Worth emphasizing is the 3rd-order risk. The evidence here, though incomplete, points in the direction of Lise (2012) discussed in subsection 3.1.2. The finding suggests that most of the observed third-order earnings risk belongs to permanent and full-time employees. This in turn is driven by wage changes which can be due to job loss (and relocation to a lower paid job), though we cannot rule out other factors such as job switching (voluntary) and health shocks for the older cohort. For Australian permanent and full-time primary earners, in particular, the third-order risk does not appear to be persistent (see the 3-year average statistics of Figure D.1). The story by Huckfeldt (2018) that workers are entrenched in low-skilled industries does not seem to hold in this case (if we consider wages as signaling low-skilled and high-skilled workplace). On the flip side, it also means that the observed persistent hour and earnings risks in 4 is the dynamics of the upper income casual and part time employees.

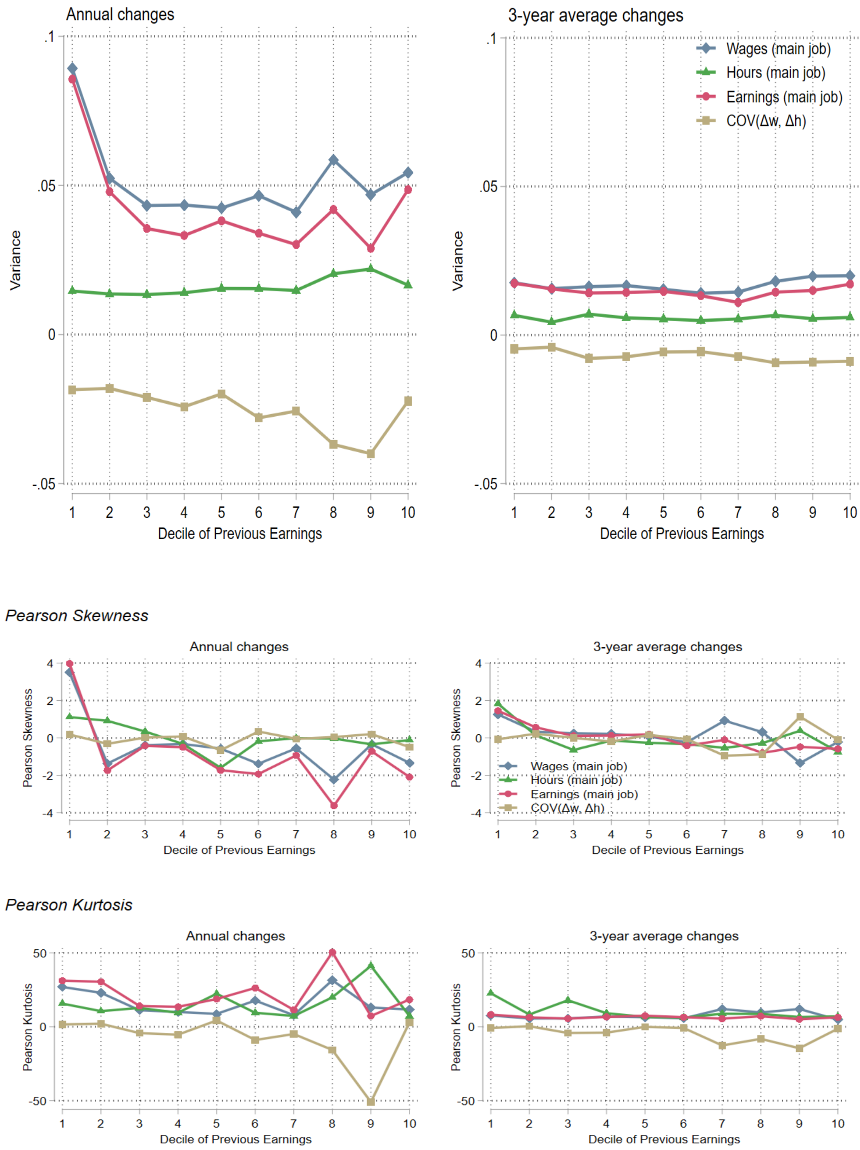

Figure D.1: Decomposition of second-order (top panel) and higher-order (bottom panel) moments of earnings shocks for permanent and full-time employees of non-own and non-family businesses

Figure D.2 corroborates the above results. It shows that for full time and permanent employees, both negative and positive earnings shocks are driven exclusively by the change in wages. The hour role is silent.

What factors account for this observation is a question not addressed in this study. Still, we think this findings point to an important direction as they reveal two types of low income workers that exhibit similar earnings dynamics driven by different mechanisms. On the one hand, we have the low income casual and part time employees whose wage and hour growths play equal role in driving the

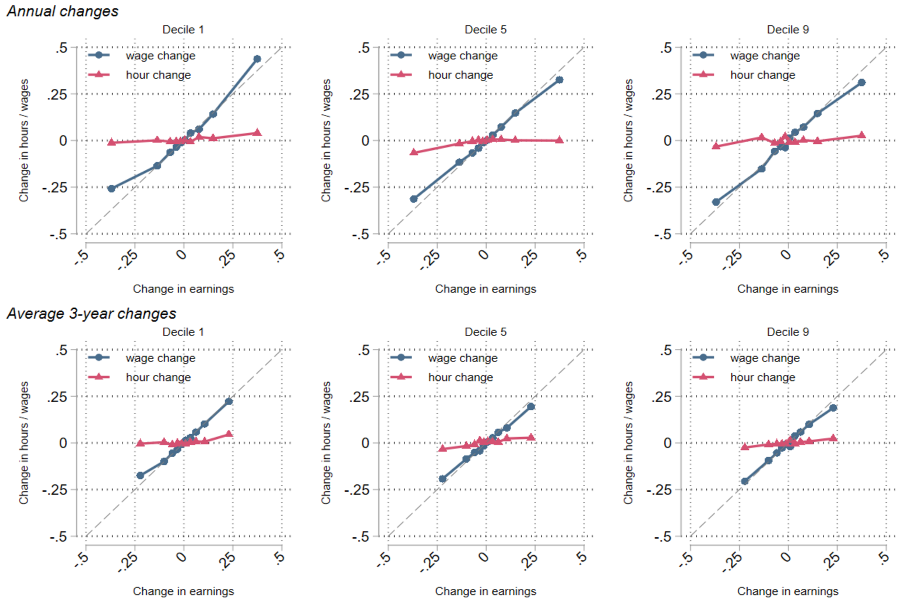

Figure D.2: Average wage and hour changes against decile of earnings shocks by selected (1st, 5th and 9th) decile of past income group of permanent and full-time employees in non-own and non-family businesses

earnings process. On the other hand, we have the low income permanent and full time employees whose earnings process is driven almost exclusively by wage growth. The same can be said for the rest of the income group, but to a lesser degree. Based on this preliminary evidence, we speculate that casual and part-time industries could be the reason behind the observed differences between Australia and other OECD nations previously examined by the literature.

Furthermore, as to why wages drive the earnings dynamics for full-time and permanent workers in Australia across income status is another worthwhile research avenue because of its influence on the evolution of inequality over time. If we know more precisely where the labour market rigidity stems from, then loosening the rigidity and allowing hours to take up a greater role could not only change the dynamics of income distribution but perhaps also the output efficiency.

E An estimation of the earnings shock process

In this section, we follow a similar approach as in Guvenen et al. (2021) and explore whether their benchmark econometric model can produce a good match of the Australian earnings process.

Econometric model. We provide a brief description of the benchmark model in Guvenen et al. (2021). The earnings process has a proposed parametric form of $\tilde{Y}_t^i = (1-\nu_t^i)e^{(g(j)+\alpha^i+\beta^i t+z_t^i+\varepsilon_t^i)}$ for individual i at time t which contains by five key constituents: (i) persistent shock z_t^i, (ii) transitory shock ε_t^i, (iii) nonemployment duration ν_t^i, (iv) individual fixed effects α^iandβ^i, and (v) deterministic age-profile of earnings $g(j)$.[33] Specifically,

(i) the persistent shock z_t^i is governed by an $AR(1)$ process

$$z_t^i \;=\; \rho z_{t-1}^i + \eta_t^i$$

with an initial condition $z_0^i \sim \mathcal{N}(0, \sigma_{z,0})$. The term η_t^i represents normal mixture innovations

$$\eta_t^i \sim \begin{cases} \mathcal{N}_{\eta,1}\left(\mu_{\eta,1}, \sigma_{\eta,1}\right) & \text{with probability } p_z \\ \mathcal{N}_{\eta,2}\left(\mu_{\eta,2}, \sigma_{\eta,2}\right) & \text{withprobability} 1-p_z \end{cases}$$

where $\mu_{\eta,1}p_z + \mu_{\eta,2}(1-p_z) = 0$ and $\mu_{\eta,1} < 0$;

(ii) the transitory shock ε_t^i is drawn from mixture of normals

$$\varepsilon_t^i \sim \begin{cases} \mathcal{N}_{\varepsilon,1}\left(\mu_{\varepsilon,1}, \sigma_{\varepsilon,1}\right) & \text{with probability } p_\varepsilon \\ \mathcal{N}_{\varepsilon,2}\left(\mu_{\varepsilon,2}, \sigma_{\varepsilon,2}\right) & \text{withprobability} 1-p_\varepsilon. \end{cases}$$

where $\mu_{\varepsilon,1}p_\varepsilon + \mu_{\varepsilon,2}(1-p_\varepsilon) = 0$ and $\mu_{\varepsilon,1} < 0$;

(iii) the nonemployment duration (i.e., the waiting time between employments) ν_t^i acts to scale the income level $\tilde{Y}_t^i$. An agent i and time t faces a time-and-persistent-shock-dependent nonemployment shock probability, $p_\nu(t, z_t^i)$, described by a logistic function. If one falls into a nonemployment spell, the duration of nonemployment ν_t^i is then drawn from an exponential distribution with mean $\frac{1}{\lambda}$ and is capped at 1 (at which point the resultant income $\tilde{Y}_t^i = 0$). That is,

$$\nu_t^i \sim \begin{cases} 0 & \text{with probability } 1-p_\nu(t, z_t^i) \\ min\{1, exp(\lambda)\} & \text{withprobability} p_\nu(t, z_t^i) \end{cases}$$

The probability of nonemployment shock is $p_\nu(t, z_t^i) = \dfrac{e^{\xi_t^i}}{1+e^{\xi_t^i}}$ where $\xi_t^i = a + bt + cz_t^i + dz_t^i t$;

(iv) the individual fixed effects α^i and β^i are ex-ante heterogeneity parameters that determinine the level and growth rates of earnings. The pair is drawn from a joint normal distribution as follows

$$\begin{bmatrix} \alpha^i \\ \beta^i \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\alpha^2 & cov_{\alpha,\beta} \\ cov_{\alpha,\beta} & \sigma_\beta^2 \end{bmatrix} \right); \text{and}$$

[33] For a comprehensive treatment of the subject, we refer the interested readers to Guvenen et al. (2021), page 25-39.

(v) a quadratic polynomial of age $g(j) = a_0 + a_1 j + a_2 j^2$ governs the deterministic lifecycle earnings profile common to all individuals where j is age of individual i at time t.

In total, the full-fledged model by Guvenen et al. (2021) requires 21 parameters.

Method of simulated moments. Guvenen et al. (2021) use the Method of Simulated Moments (MSM). They begin the procedure with a simple linear-Gaussian model and incrementally add new features described above. There are five sets of target moments and a weighting matrix that reflects their subjective beliefs on the importance of each set of moments. This piecemeal construction of the benchmark specification allows them to better understand how each component contributes to the dynamics of the simulated earnings process. They find that the MSM provides a good fit to the data at a relatively low computational burden.

We follow Guvenen et al. (2021) and estimate the benchmark specification using the MSM. In our estimation we target four sets of moments:

1. Cross-sectional moments of earnings changes. We target the mean, standard deviation, skewness, and kurtosis of one- and three-year average earnings changes for each of 4 age groups and for each of 10 earnings groups, giving us $3 \times 2 \times 5 \times 10 = 300$ cross-sectional moments,

2. Impulse response moments (i.e., expected k-period future earnings changes for $k = 1, 2, 3, 5$,and 10) by quintile of previous year changes and decile of previous market income, giving us $5 \times 5 \times 10 = 250$ moments, and

3. Average years of non-employment by 4 age groups and 10 earnings groups, giving us 40 moments.

4. Variance of log earnings by 4 age groups and 10 earnings groups; thus another set of 40 moments.

In the MSM procedure, we estimate the 21 parameters of the benchmark process by minimizing the weighted sum of squared percentage deviations from targeted moments. Unlike in Guvenen et al. (2021) in which weighting matrix (W) is based on their belief and experience gained from numerous trials and errors, we employ the iterated variance-covariance method to arrive at the optimal weighting matrix, W^*. We begin by setting the identity matrix as our initial guess of $\hat{W}^*$. Given $\hat{W}^*$, we estimate the parameters of interest and calculate a vector of moment error functions e using the percent difference in the vector of simulated moments from the data moments. Then, the vector e is used to construct a variance-covariance matrix whose inverse is our next candidate for $\hat{W}^*$. This procedure is repeated until some i^{th} iteration when the estimated optimal weighting matrix $\hat{W}^*$ no longer changes (i.e., $||\hat{W}_i - \hat{W}_{i-1}|| < \varepsilon$where the norm of choice is the root mean squared relative error or $RMSRE$).

Data limitation. One challenge of the current study is the lack of market earnings and employment data from HILDA to cover the entire lifespan of individuals. This limitation means that certain informative moments such as those related to earning growth and distribution of total years employed over the entire lifetime of individuals are not available. Thus, we do not fit the model to the life-cycle earnings growth or nonemployment distribution in this attempt. However, we find that the third set of moments, the average years of non-employment by age cohort and income group, is a good compromise and helps us achieve a closer match between the simulated second- and higher-order transitory and persistent risks and those observed in the data.

Another challenge is that MSM is a moment-matching exercise and therefore relies heavily on accurate data moments. Because the primary objective of the paper is to broadly understand the earnings dynamics and insurance, HILDA is the dataset of choice as it contains many identifiers and covariates indispensable to the main study. The drawback is that HILDA only has 20 years of observations, which places a restriction on our ability to estimate the earnings shock process via parametric specifications, particularly if the goal is to capture the third- and fourth-order moments of persistent shocks. Since persistent risks rely on some form of temporal aggregates, a 20-period dataset only allows us to compute up to 3-year average shocks instead of 5-year averages as Guvenen et al. (2021) do, or else, would have to contend with the myriads of issues associated with small sample size. Even then, we see that the fourth-order moments of 3-year average shocks behave more erratically and likely stray from the true patterns, which is a concern for two reasons. First, the output simulated moments can only be as accurate and representative as the input data moments they approximate. Second, parameter estimates associated with persistence can be sensitive to the input data moments. Large fluctuations in the third- and fourth-order moment values thus make it difficult to match the skewness and kurtosis of the residual income shock distribution.[34]

Results. Our estimated results are reported in Table E.1 and Figure E.1.

Parameters		Values	Parameters		Values
Persistent shock	ρ	0.7426	Nonemployment	λ	0.0668
	$\sigma_{z,0}$	1.4995		a	-0.2020
	ρ_z	0.9297		b	-0.0889
	$\mu_{\eta,1}$	-0.0049		c	-0.0983
	$\sigma_{\eta,1}$	0.3042		d	-0.0528
	$\sigma_{\eta,2}$	0.1918	Ex-ante heterogeneity	σ^2_α	0.0029
Transitory shock	ρ_ε	0.9498		σ^2_β	0
	$\mu_{\varepsilon,1}$	0.7358		$cov_{\alpha,\beta}$	0.3784
	$\sigma_{\varepsilon,1}$	0.1419	Quadratic polynomial of age	a_1	0.0108
	$\sigma_{\varepsilon,2}$	0.9273		a_2	-0.0001

Table E.1: Estimated parameters of the benchmark model

Notes: The quadratic polynomial term a_0 is turned off (set to zero). Multiple runs indicates that the inclusion of $a_0$can cause convergence problem.

Figure E.1 depicts the accomplishment and shortcomings of the current configuration and the available data. Qualitatively, the model does a good job of capturing the non-linear and non-Gaussian features of the market income shock distribution. On the contrary, the current estimation is unable to achieve a close match between the actual and simulated moment values, particularly for the second-order moments. The top-left panel of Figure E.1 indicates that the large errors are generated by the lower-peak distribution of simulated shocks (i.e., less dense about the centre) relative to that of the data. At this point, we believe that it has some connection to the issues raised earlier. First, the less well-behaved values of skewness and kurtosis might have been problematic. More precisely, the inconsistent third- and fourth-moment values by age and past income subgroups increases the difficulty of producing good matches as some parameters can be sensitive to fluctuating moment values. This might also explain why the model earnings process leads to unusual bumps in the simulated shock distribution in its attempt to capture the L-shaped left skewness and the hump-shaped excess kurtosis over income decile. Second, the absence of life-cycle earnings growth moments from the data to discipline the parameters might have made it possible for the estimation process to generate higher

[34] The fact that their qualitative patterns match well with those from the previous studies and remain consistent across settings assures us that they represent the income process in the data. Notwithstanding, this does not tell us about the accuracy of the estimates. The MSM procedure requires more accurate moment estimates from a larger dataset.

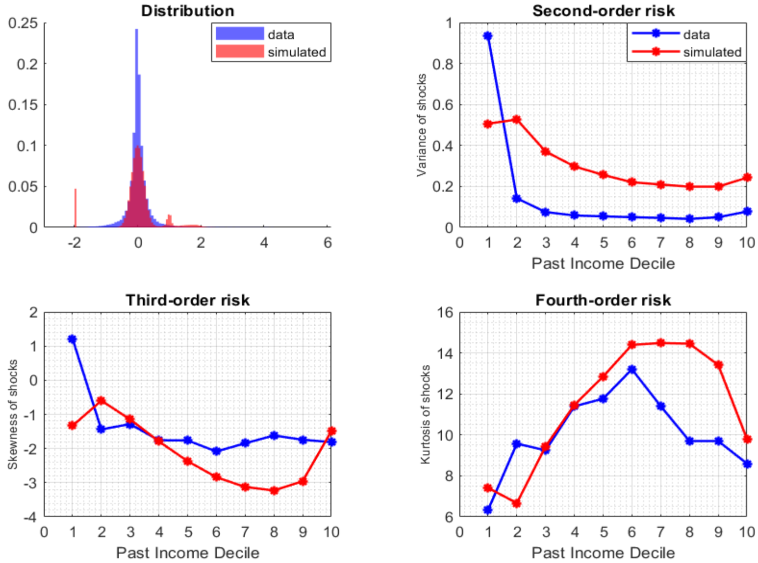

Figure E.1: Actual vs. simulated results

residual shock volatility (top-right panel) at the cost of unrealistic earnings growth by weighting the estimation errors for second moments down.

Despite the mismatches, the exercise speaks for the capability of the parametric model proposed by Guvenen et al. (2021) in estimating the non-linear and non-Guassian earnings process. We believe improvement is a certainty with more trials and errors and a larger dataset. Another key lesson is that even without substantial knowledge of the data moments and their connections to the benchmark parameters that would have permitted one to assign subjective weights to each set of moments, we were able to operate the MSM estimation procedure by employing the iterated variance-covariance method to arrive at the optimal weighting matrix. On top of convenience, the iterative approach proved to be a useful tool under time constraint and limited computational power by allowing us to more efficiently explore the parameter space, fine-tune our initial guesses, and set more informative lower and upper bounds for the optimization routine.

Hence, our estimated model is capable of reproducing the overall pattern of the key empirical facts. However, more comprehensive data sets are required to have a more accurate estimation of the non-Gaussian models of earnings dynamics in Australia.

F Additional tables and figures

F.1 Dynamics of earnings, wages and hours

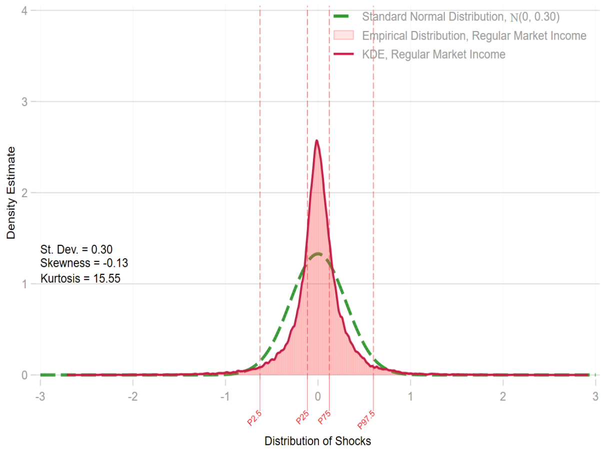

Figure F.1: Empirical distributions of 3-year average growth of individual regular market income for primary earners aged 25-64.

Second moment of regular market earnings shocks by age group via different measures

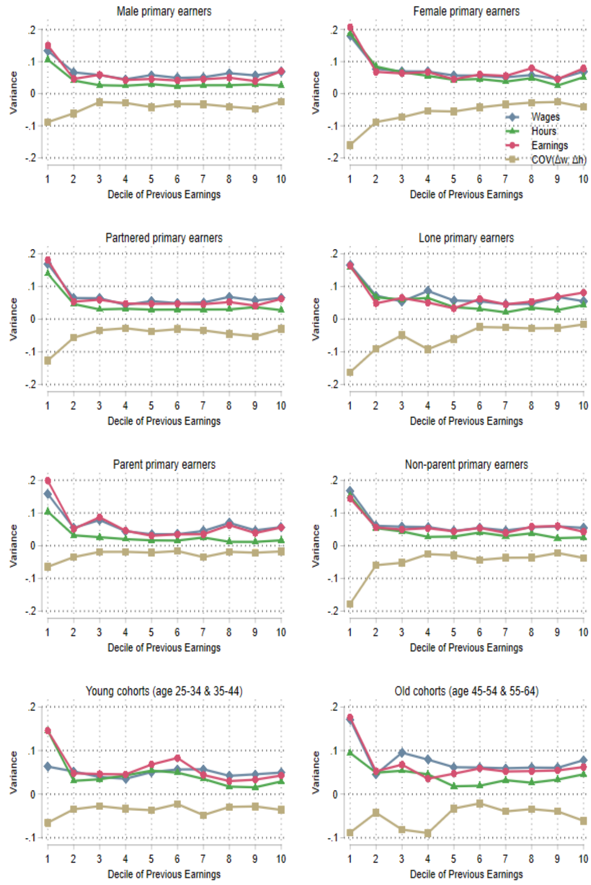

Figure F.2: Variance of annual changes in usual weekly earnings, wages, and hours of selected subsamples (including the tailends of their distributions). The graphs contain observations of selected subsamples and are restricted to individuals who report positive usual weekly earnings (work at least one day per week at or above the minimum wage rate of AU$20 in 2018 value) for at least 18 years. Similar patterns are also observed when minimum employment requirement is set to 0 (unrestricted), 10, 15, or 20 years.

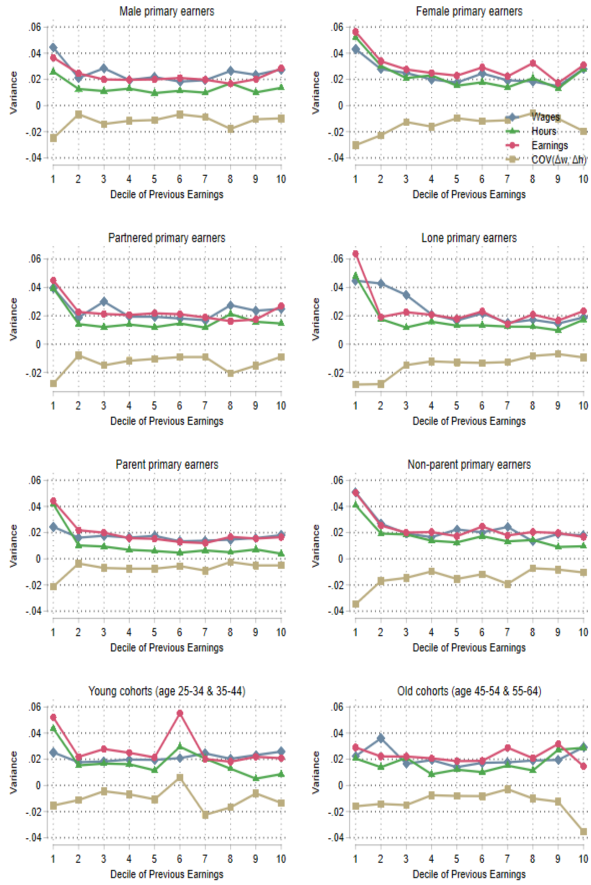

Figure F.3: Variance of 3-year average changes in usual weekly earnings, wages, and hours of selected subsamples (including the tailends of their distributions). The graphs contain observations of selected subsamples and are restricted to individuals who report positive usual weekly earnings (work at least one day per week at or above the minimum wage rate of AU$ 20 in 2018 value) for at least 18 years. Similar patterns are also observed when minimum employment requirement is set to 0 (unrestricted), 10, 15, or 20 years.

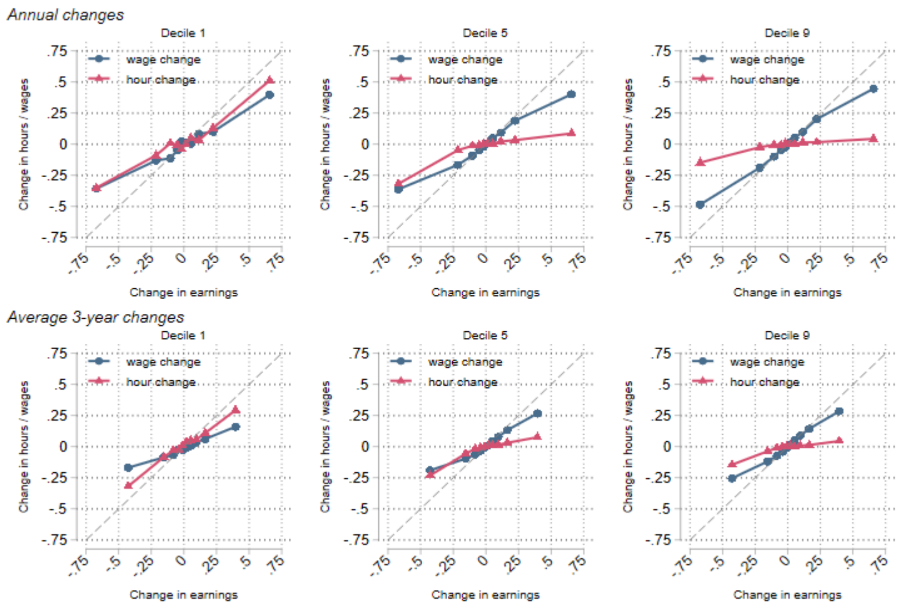

Figure F.4: Changes in residual weekly wages and hours versus decile of changes in residual usual weekly earnings (from main job) for primary earners in the 1st, 5th, and 9th deciles of past usual weekly earnings. The top and bottom panels report annual changes and 3-year average changes, respectively. We consider all primary earners regardless of their work history. Similar patterns are also observed when minimum employment requirement is set to 0 (unrestricted), 10, 15, or 20 years.

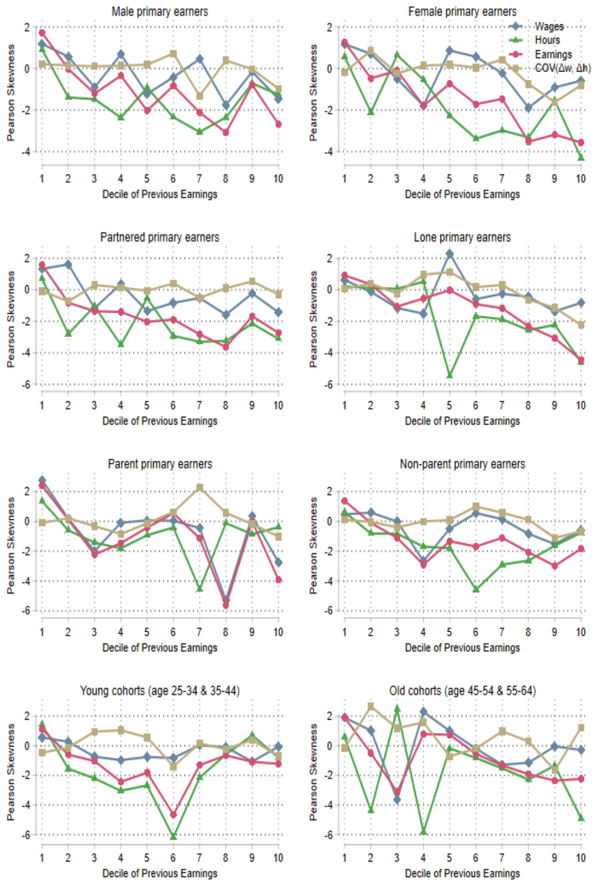

Figure F.5: Pearson skewness of annual average changes in usual weekly earnings, wages, and hours of selected subsamples (including the tailends of their distributions). The graphs contain observations of selected subsamples and are restricted to individuals who report positive usual weekly earnings (work at least one day per week at or above the minimum wage rate of AU$20 in 2018 value) for at least 18 years. Similar patterns are also observed when minimum employment requirement is set to 0 (unrestricted), 10, 15, and 20 years.

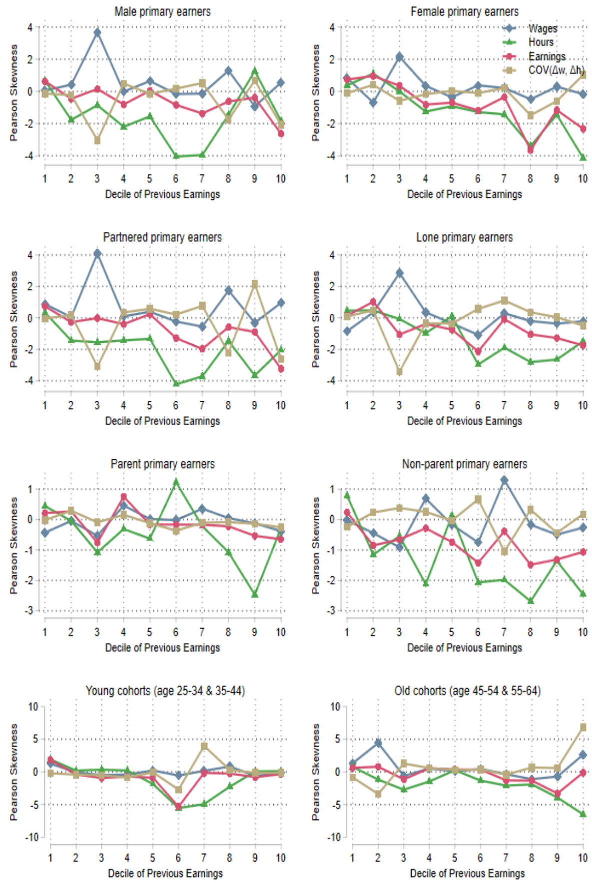

Figure F.6: Pearson skewness of 3-year average changes in usual weekly earnings, wages, and hours of selected subsamples (including the tailends of their distributions). The graphs contain observations of selected subsamples and are restricted to individuals who report positive usual weekly earnings (work at least one day per week at or above the minimum wage rate of AU$20 in 2018 value) for at least 18 years. Similar patterns are also observed when minimum employment requirement is set to 0 (unrestricted), 10, 15, or 20 years.

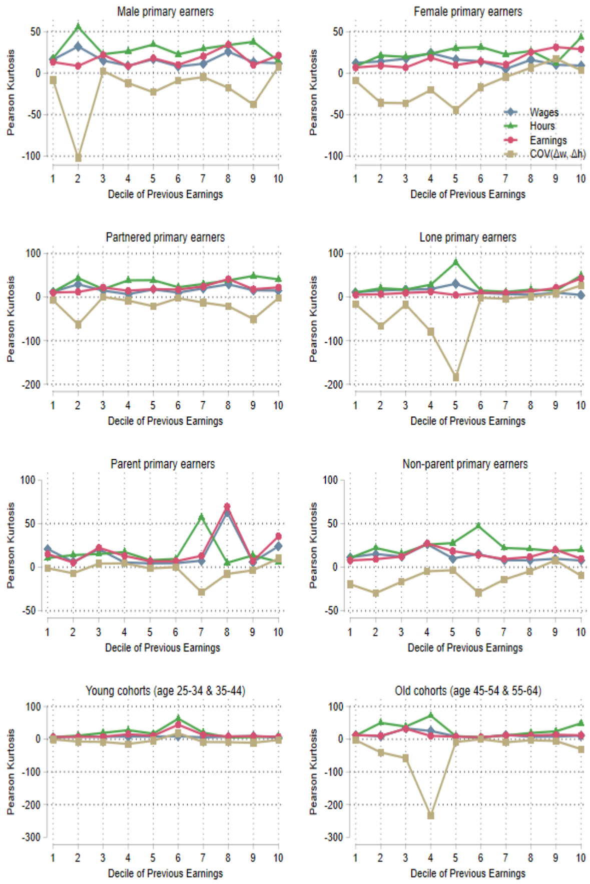

Figure F.7: Pearson kurtosis of annual changes in usual weekly earnings, wages, and hours of selected subsamples (including the tailends of their distributions). The graphs contain observations of selected subsamples and are restricted to individuals who report positive usual weekly earnings (work at least one day per week at or above the minimum wage rate of AU$ 20 in 2018 value) for at least 18 years. Similar patterns are also observed when minimum employment requirement is set to 0 (unrestricted), 10, 15, or 20 years.

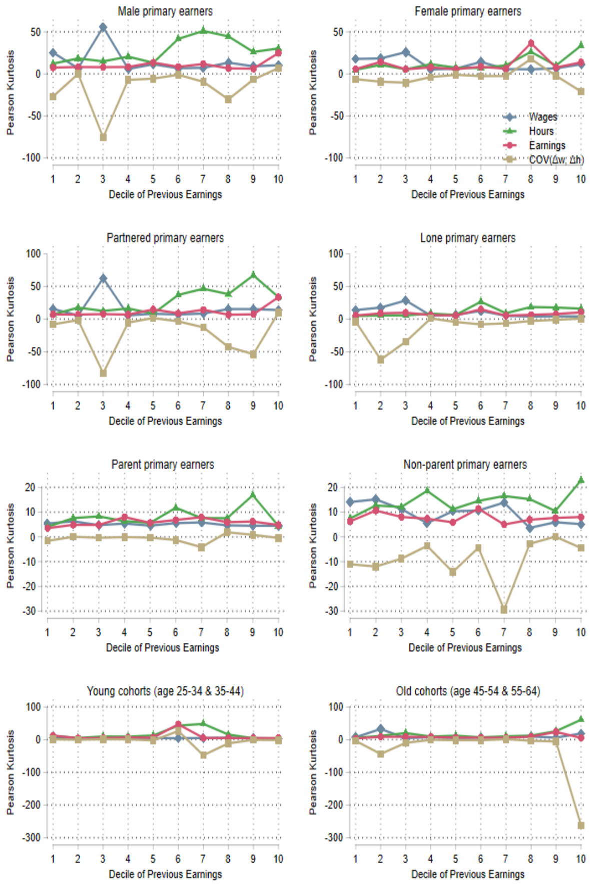

Figure F.8: Pearson kurtosis of 3-year average changes in usual weekly earnings, wages, and hours of selected subsamples. The graphs contain observations of selected subsamples and are restricted to individuals who report positive usual weekly earnings (work at least one day per week at or above the minimum wage rate of AU$20 in 2018 value) for at least 18 years. Similar patterns are also observed when minimum employment requirement is set to 0 (unrestricted), 10, 15, or 20 years.

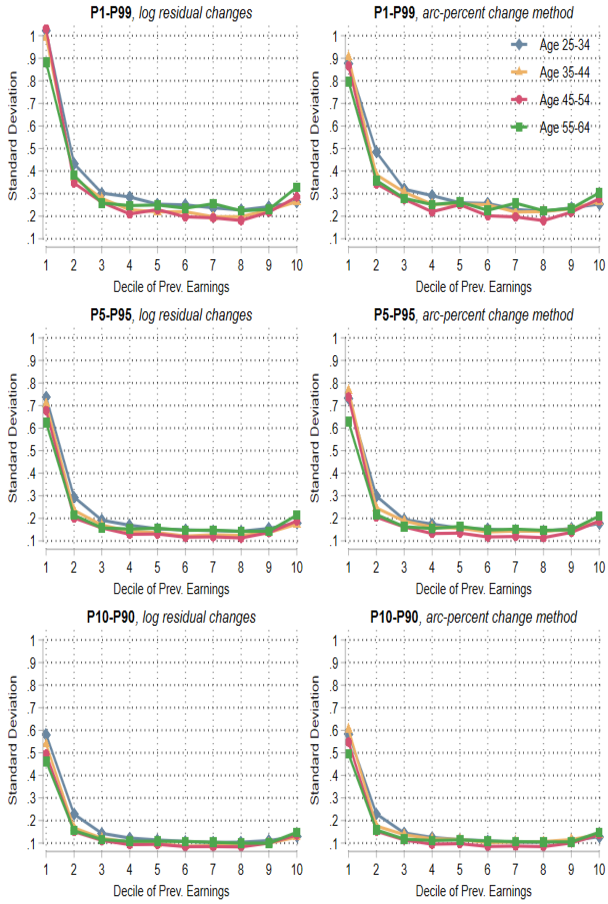

Figure F.9: Second moment statistics measured at $P1-P99$, $P5-P95$, and $P10-P90$ of the annual regular market earnings change distributions of primary earners. The left panel's annual figures are statistics of the changes in log of residual income as described in equation 1. The right panel's annual figures are statistics obtained via *Arc-Percent Change method* (i.e., statistics of mid-point averages of changes in the income-to-group-means ratio).

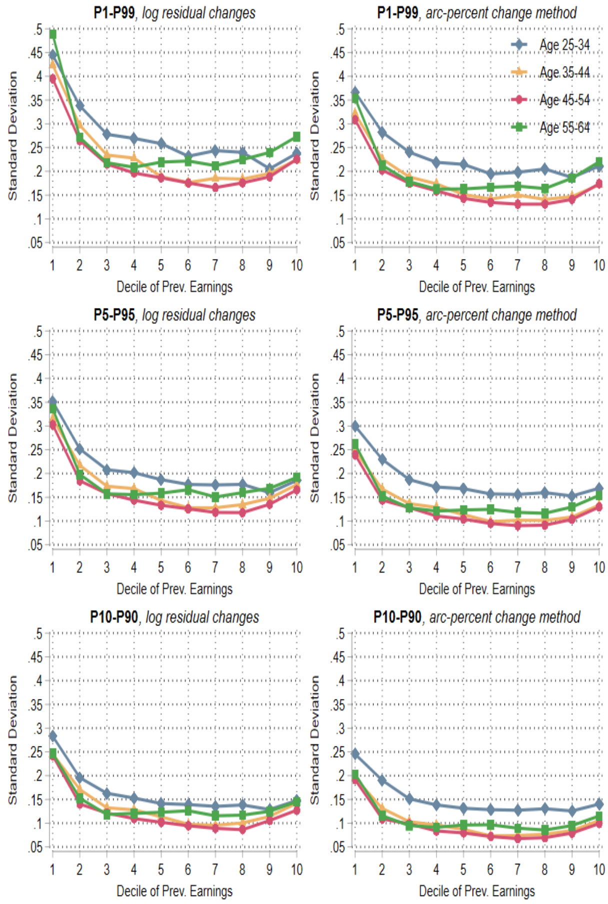

Figure F.10: Second moment statistics measured at $P1-P99$, $P5-P95$, and $P10-P90$ of the 3-year average regular market earnings change distributions of primary earners. The left panel's annual figures are statistics of the changes in log of residual income as described in equation 1. The right panel's annual figures are statistics obtained via *Arc-Percent Change method* (i.e., statistics of mid-point averages of changes in the income-to-group-means ratio).

F.2 Family insurance: Standardized and quantile-based measures

P1-P99

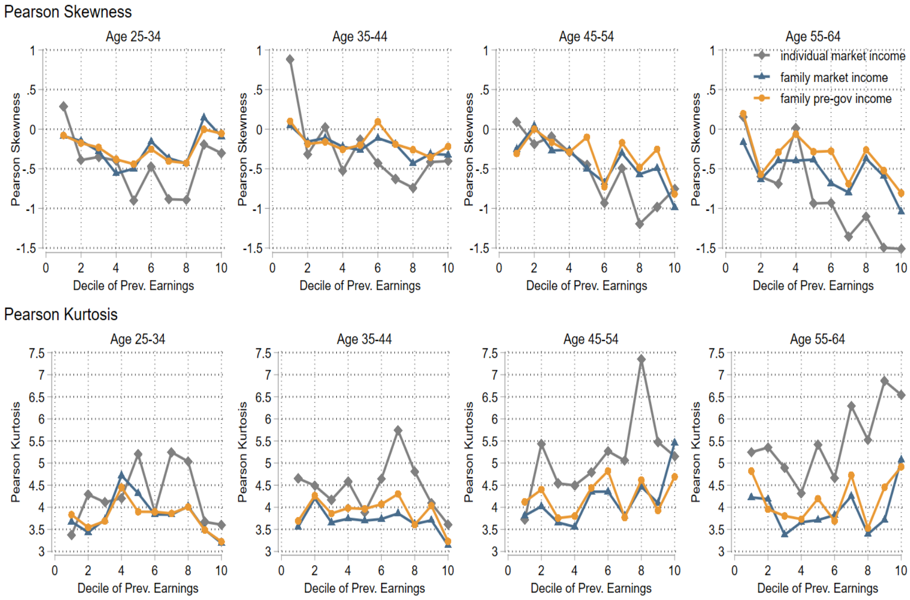

Figure F.11: Skewness and Kurtosis of the distribution of 3-year average changes of family income (P1-P99) at different levels. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

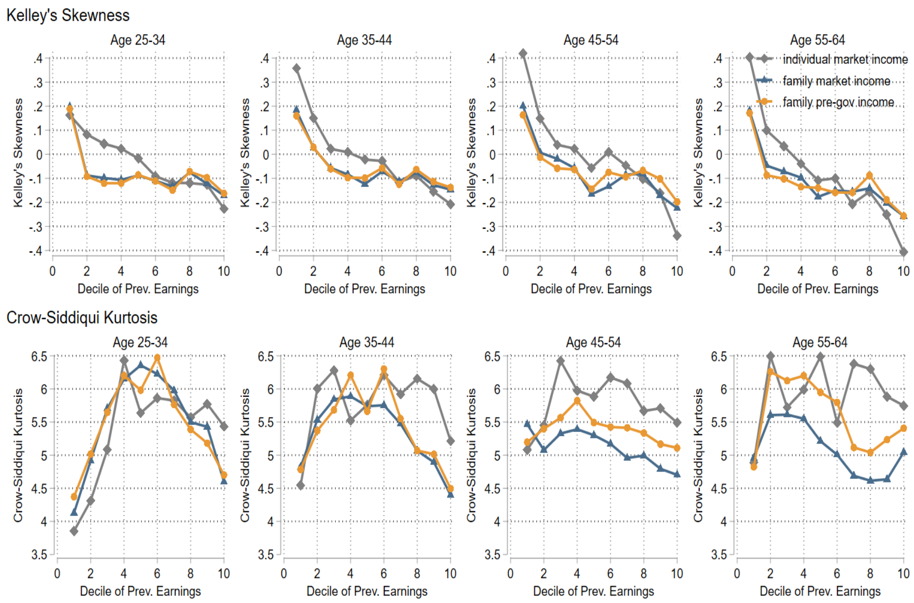

Figure F.12: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of annual changes of family income (P1-P99) at different levels. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of family pre-government income.

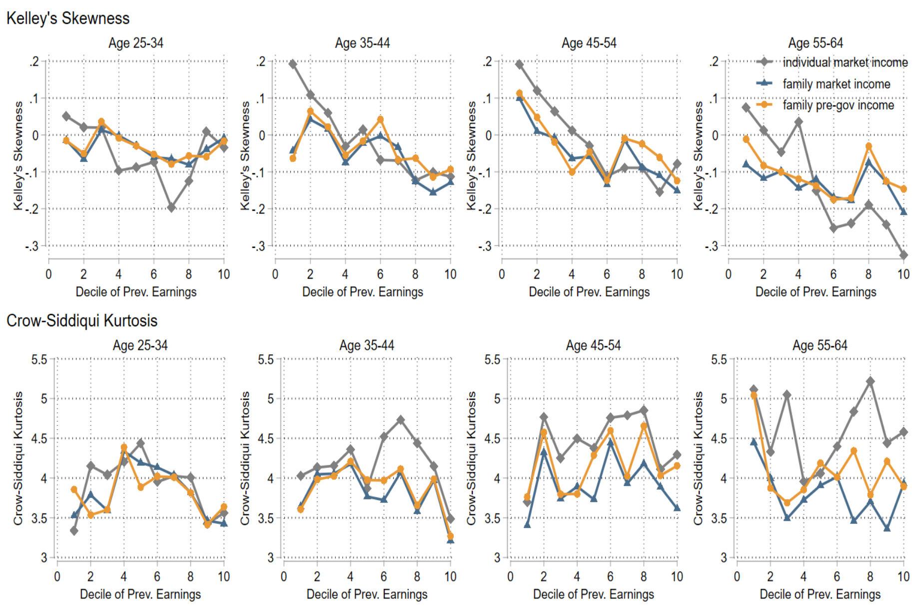

Figure F.13: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of 3-year average changes of family income (P1-P99) at different levels. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of family pre-government income.

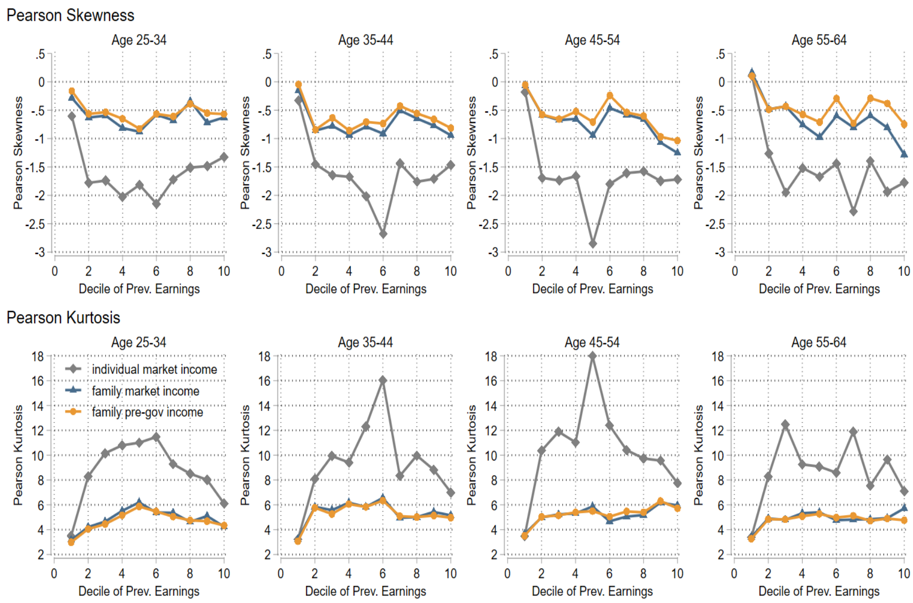

Figure F.14: Skewness and Kurtosis of the distribution of annual changes of family income (P1-P99) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

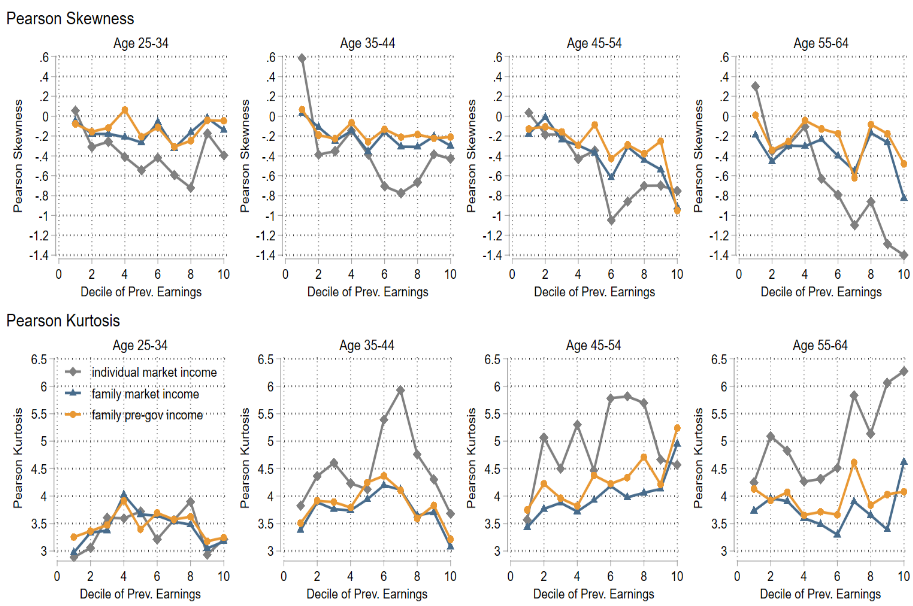

Figure F.15: Skewness and Kurtosis of the distribution of 3-year average changes of family income (P1-P99) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

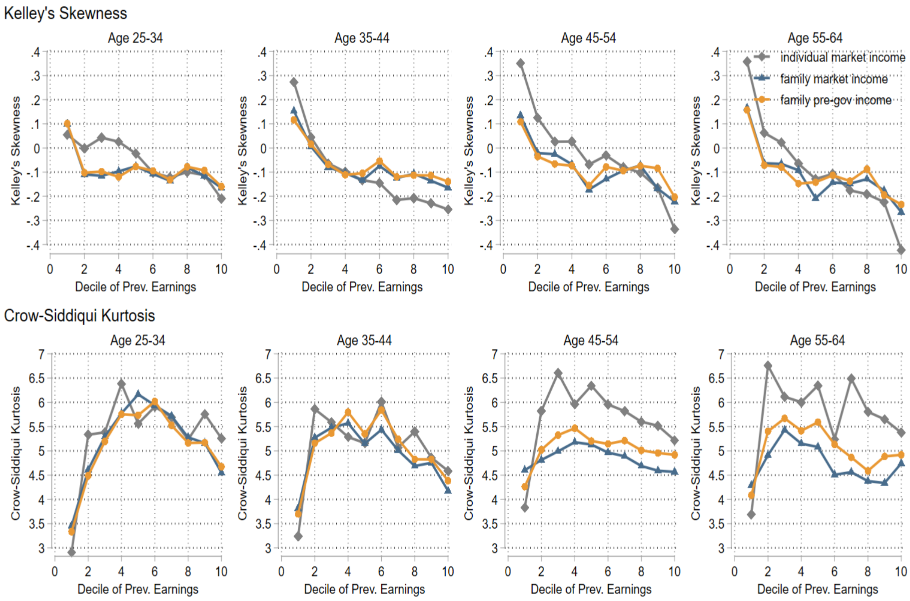

Figure F.16: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of annual changes of family income (P1-P99) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

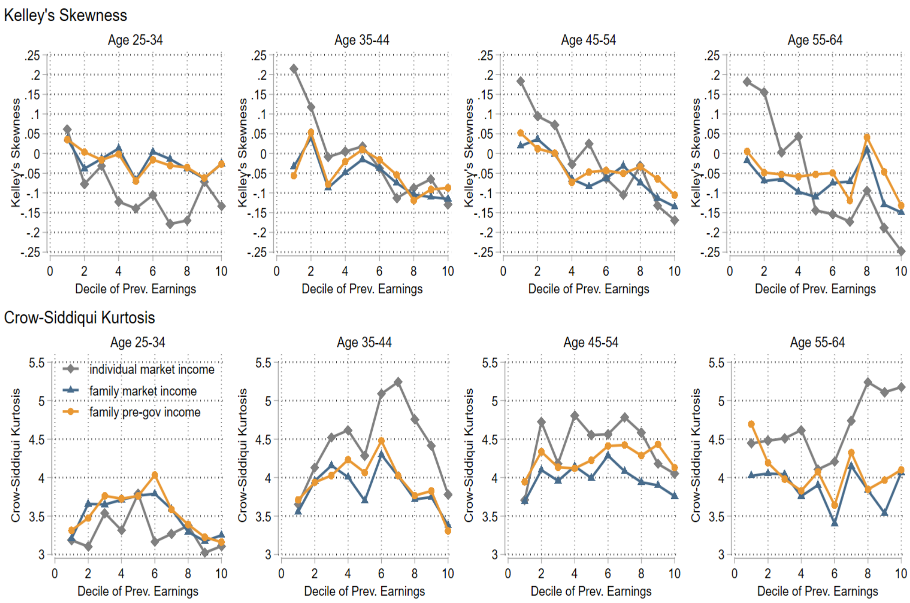

Figure F.17: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of 3-year average changes of family income (P1-P99) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

P5-P99

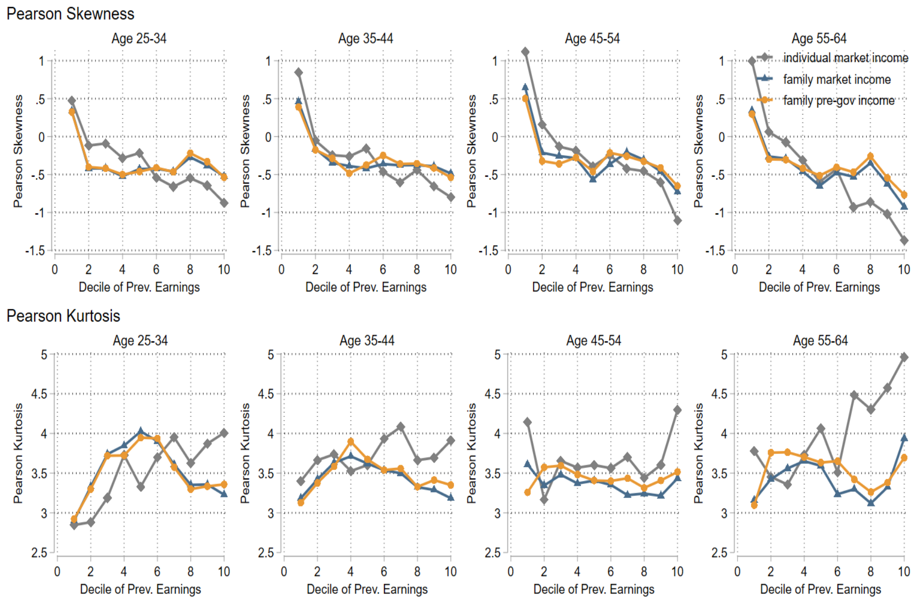

Figure F.18: Skewness and Kurtosis of the distribution of annual changes of family income (P5-P95) at different levels. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

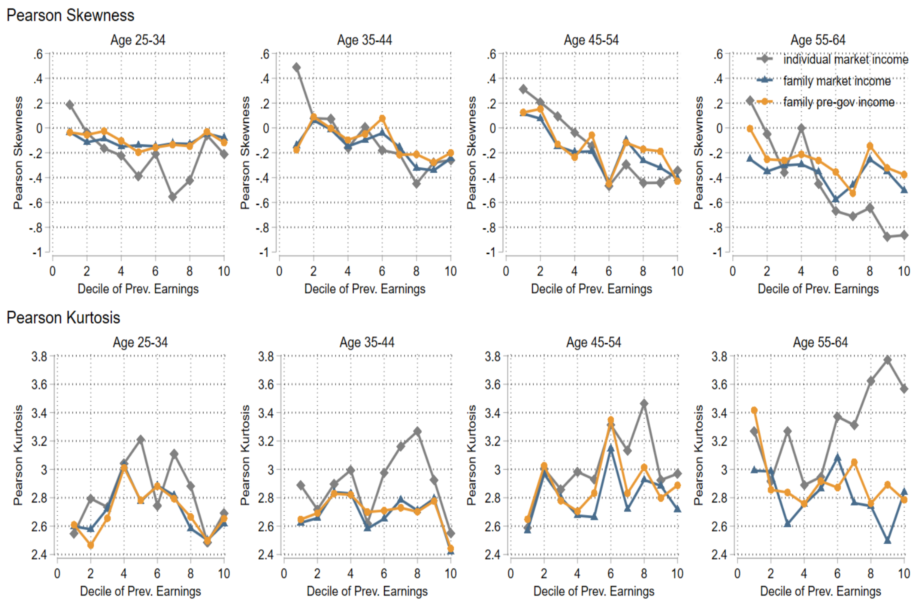

Figure F.19: Skewness and Kurtosis of the distribution of 3-year average changes of family income (P5-P95) at different levels. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

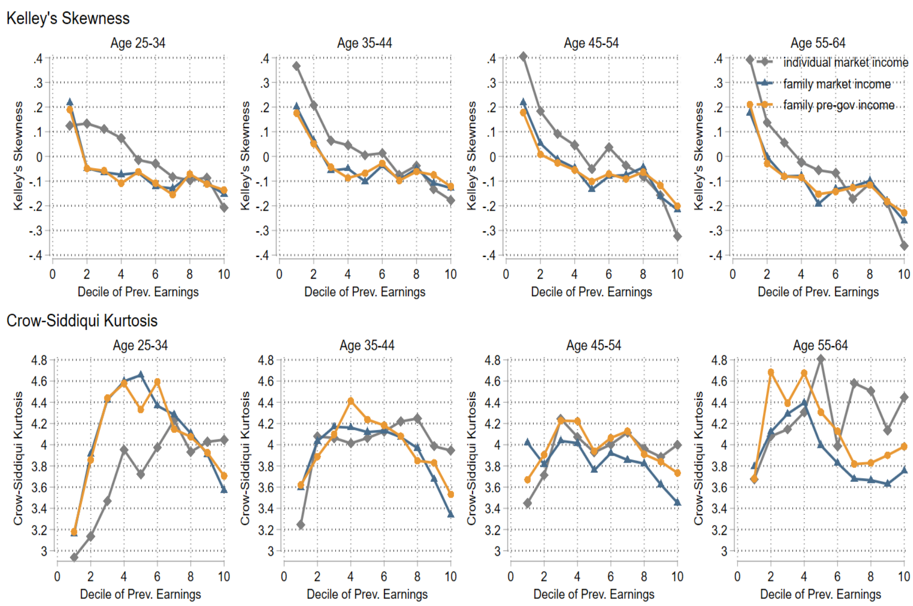

Figure F.20: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of annual changes of family income (P5-P95) at different levels. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of family pre-government income.

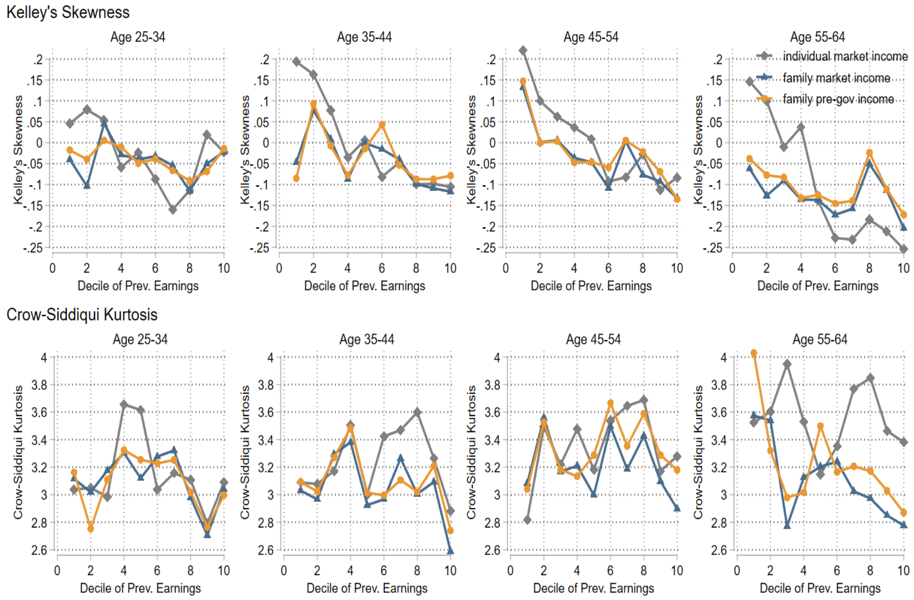

Figure F.21: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of 3-year average changes of family income (P5-P95) at different levels. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of family pre-government income.

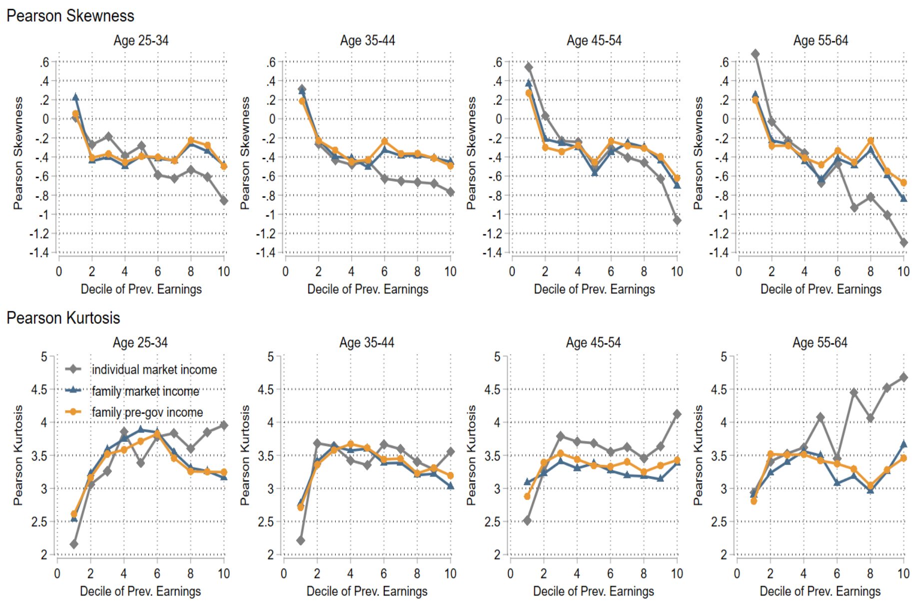

Figure F.22: Skewness and Kurtosis of the distribution of annual changes of family income (P5-P95) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

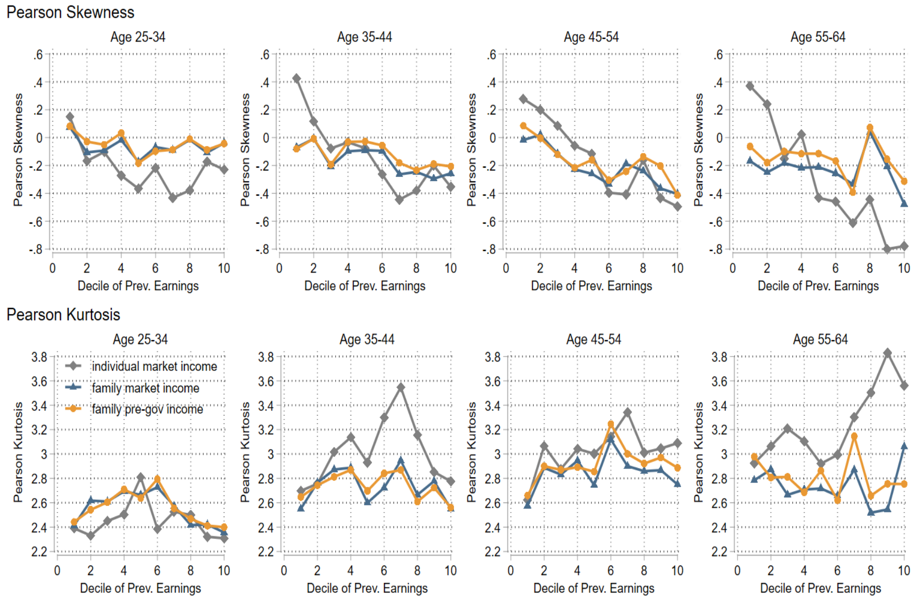

Figure F.23: Skewness and Kurtosis of the distribution of 3-year average changes of family income (P5-P95) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

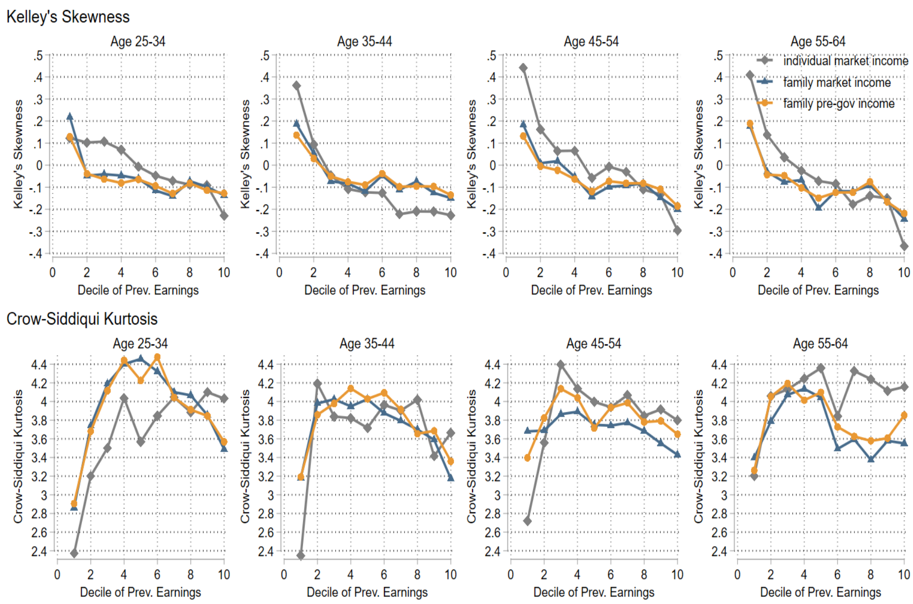

Figure F.24: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of annual changes of family income (P5-P95) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

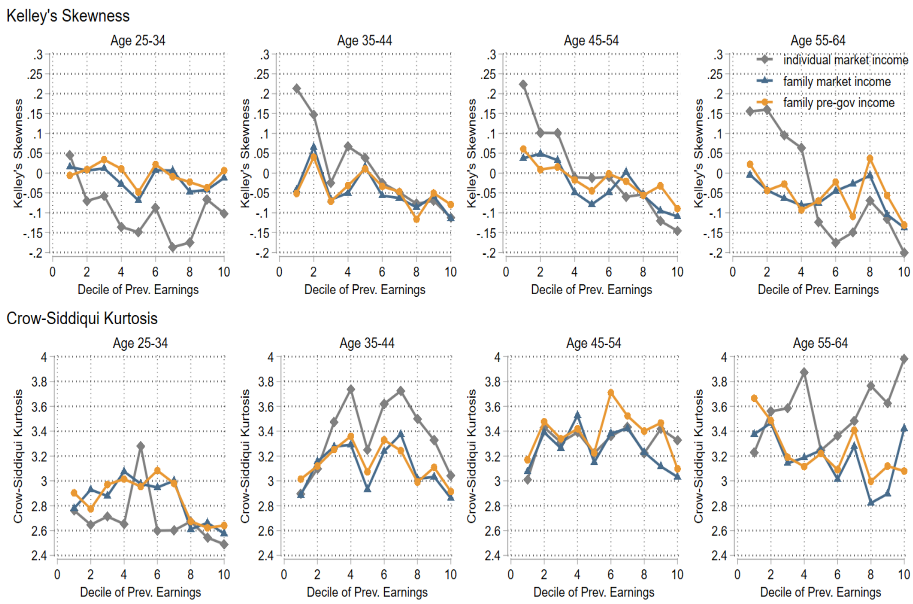

Figure F.25: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of 3-year average changes of family income (P5-P95) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of family market income and private transfer to the third- and fourth-order risks of pre-government family income.

F.3 Government insurance: Standardized and quantile-based measures

Second moment (P1-P99)

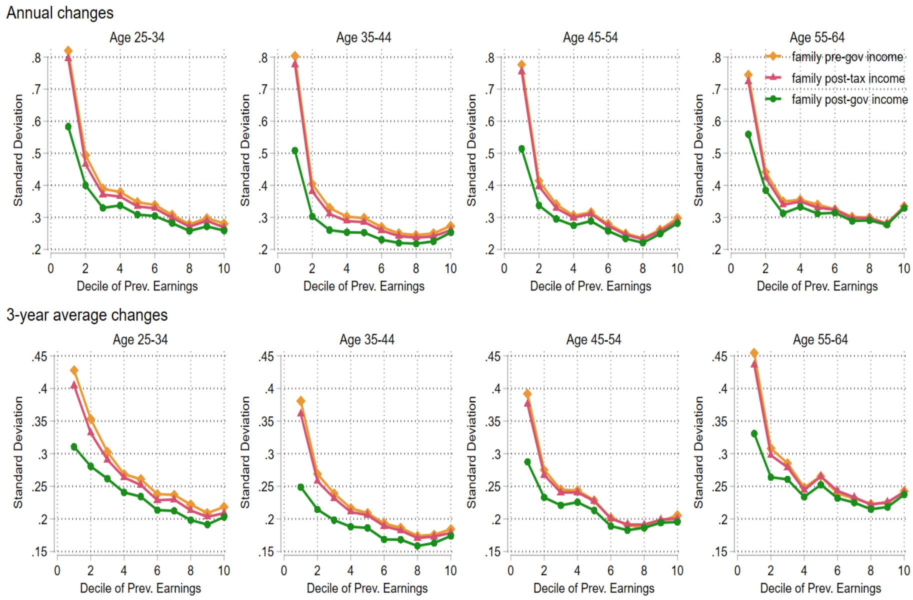

Figure F.26: Standard deviation of the distribution of annual and 3-year average changes of family income (P1-P99) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the second-order risk of disposable family income.

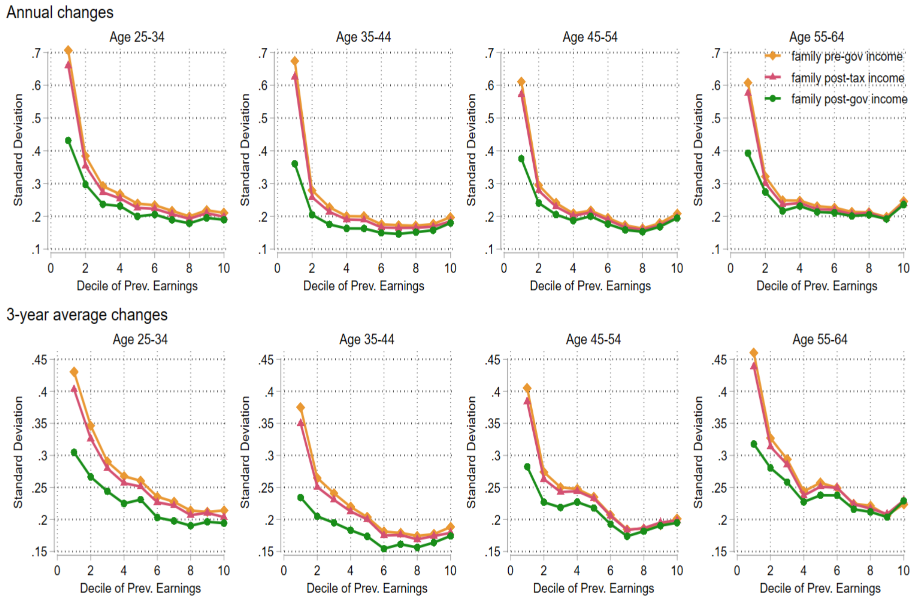

Figure F.27: Standard deviation of the distribution of annual and 3-year average changes of family income (P5-P95) at different levels. The figure captures the relative contribution of tax and transfer to the second-order risk of disposable family income.

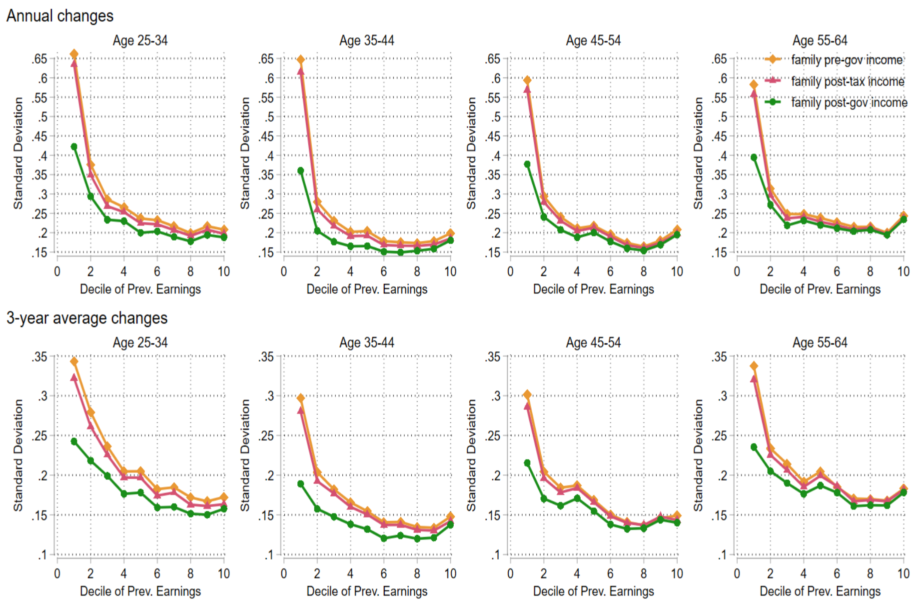

Figure F.28: Standard deviation of the distribution of annual and 3-year average changes of family income (P5-P95) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the second-order risk of disposable family income.

Higher-order moments (P1-P99)

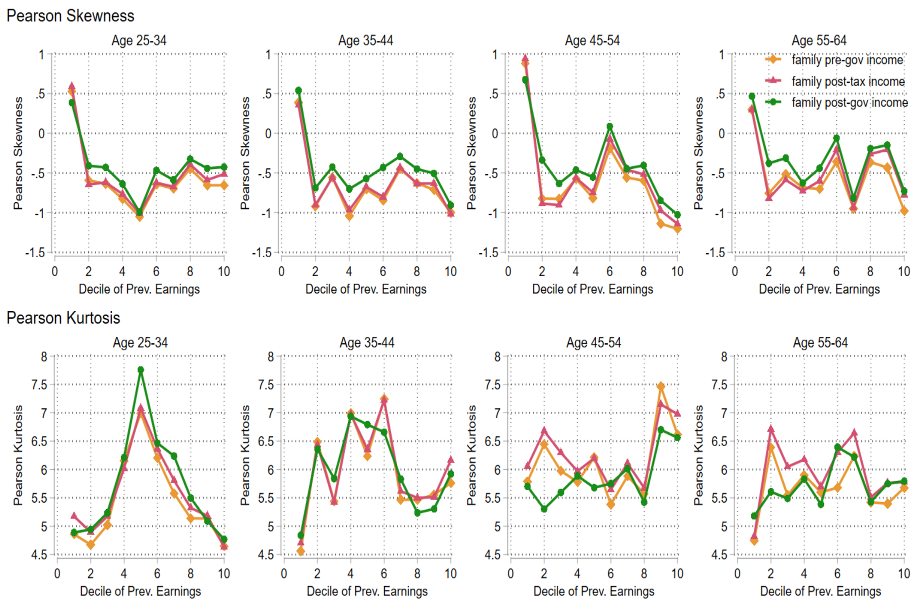

Figure F.29: Skewness and Kurtosis of the distribution of annual changes of family income (P1-P99) at different levels. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

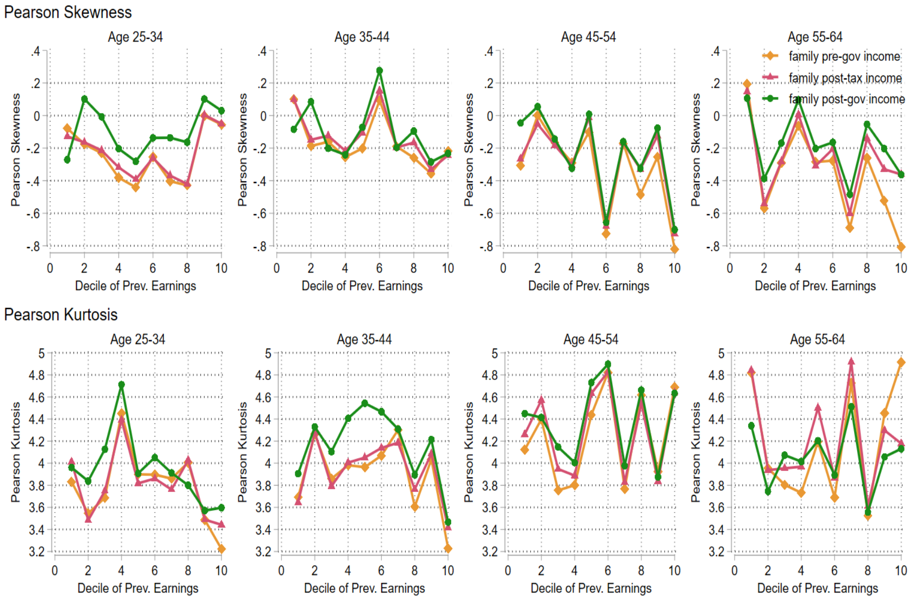

Figure F.30: Skewness and Kurtosis of the distribution of 3-year average changes of family income (P1-P99) at different levels. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

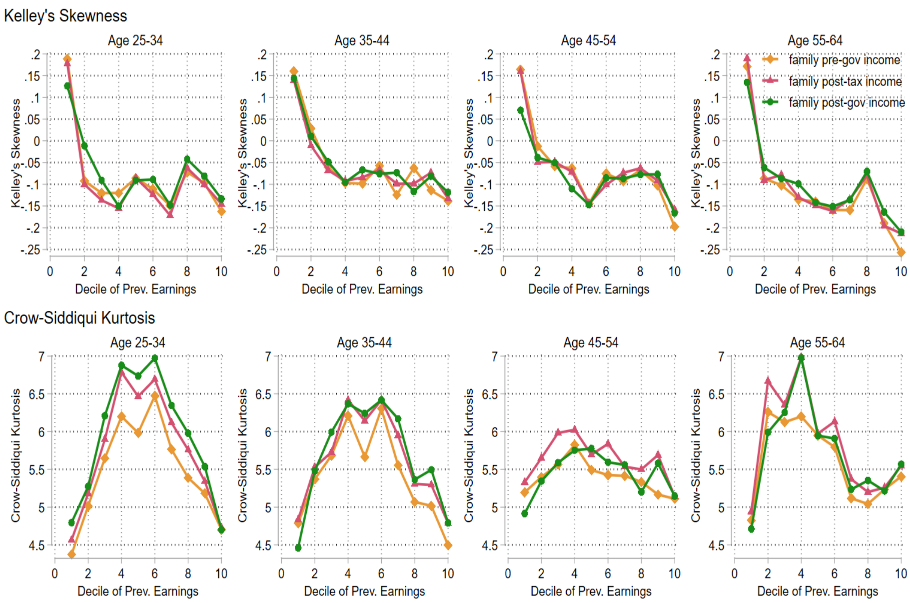

Figure F.31: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of annual changes of family income (P1-P99) at different levels. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

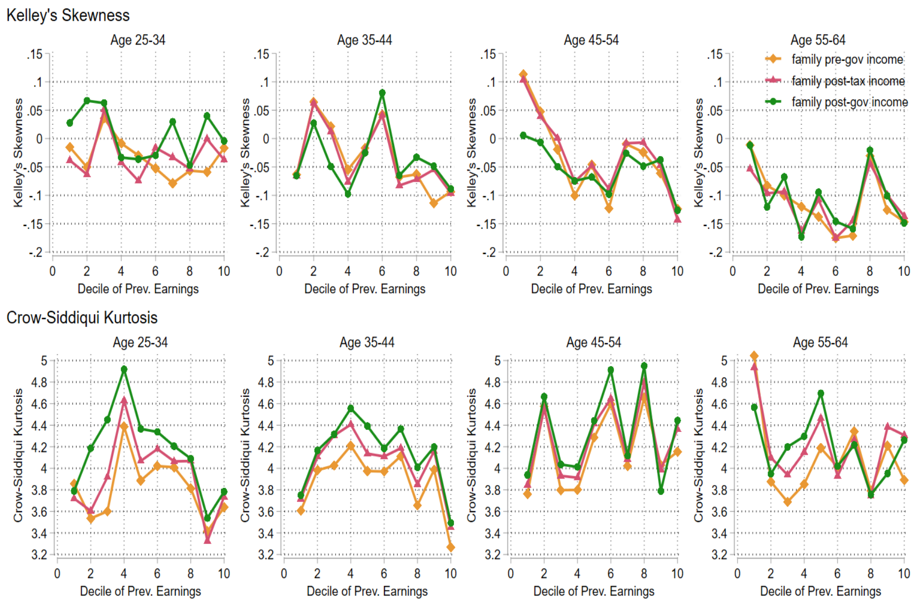

Figure F.32: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of 3-year average changes of family income (P1-P99) at different levels. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

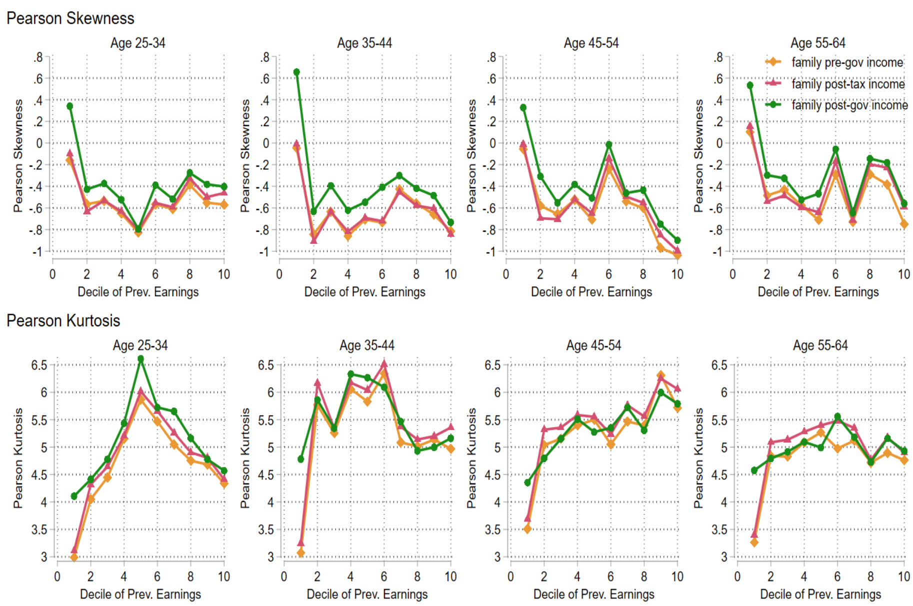

Figure F.33: Skewness and kurtosis of the distribution of annual changes of family income (P1-P99) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

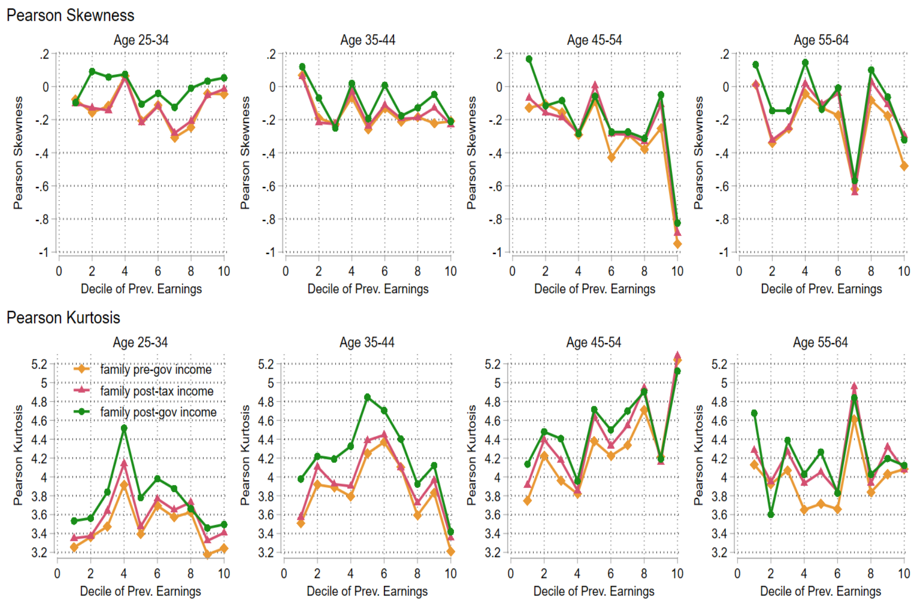

Figure F.34: Skewness and kurtosis of the distribution of 3-year average changes of family income (P1-P99) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

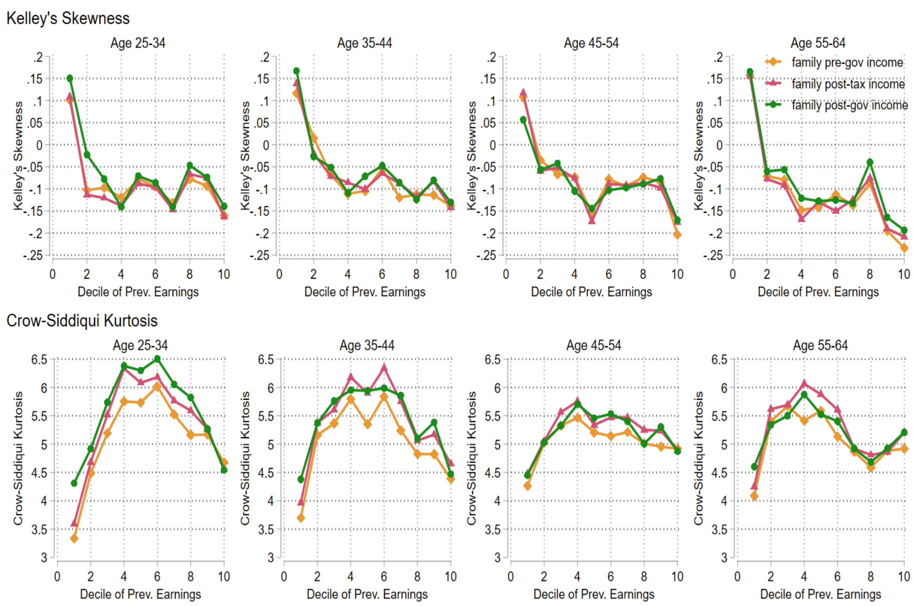

Figure F.35: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of annual changes of family income (P1-P99) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

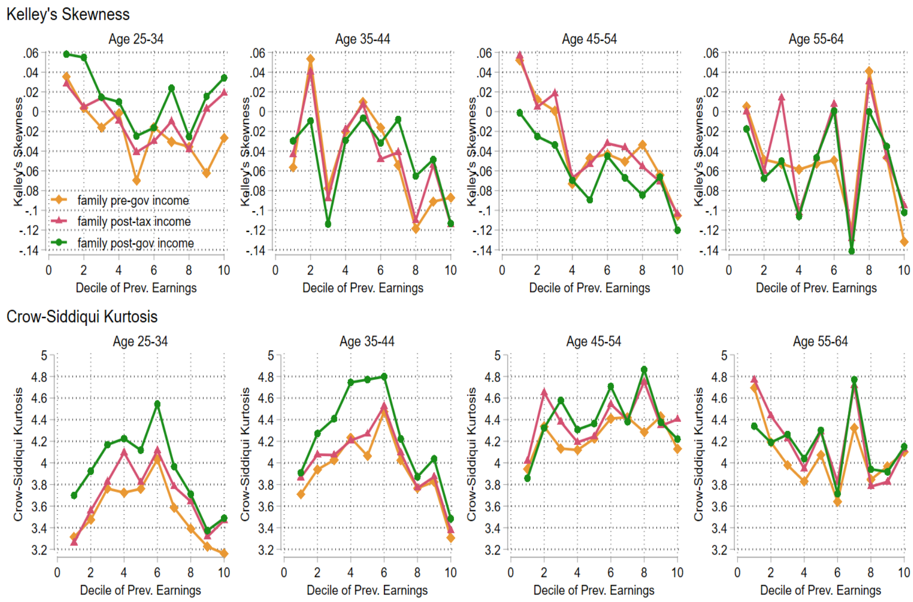

Figure F.36: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of 3-year average changes of family income (P1-P99) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

Higher-order moments (P5-P95)

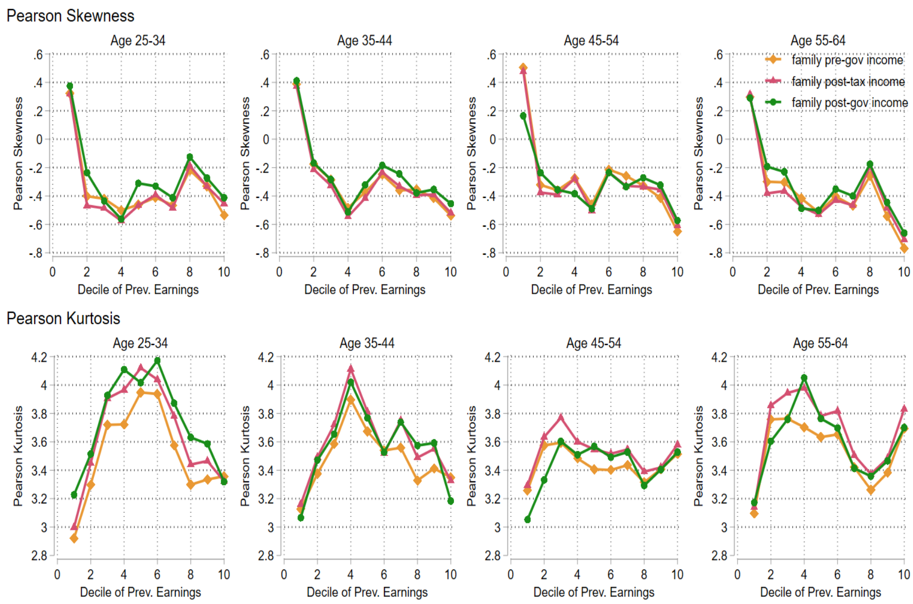

Figure F.37: Skewness and Kurtosis of the distribution of annual changes of family income (P5-P95) at different levels. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

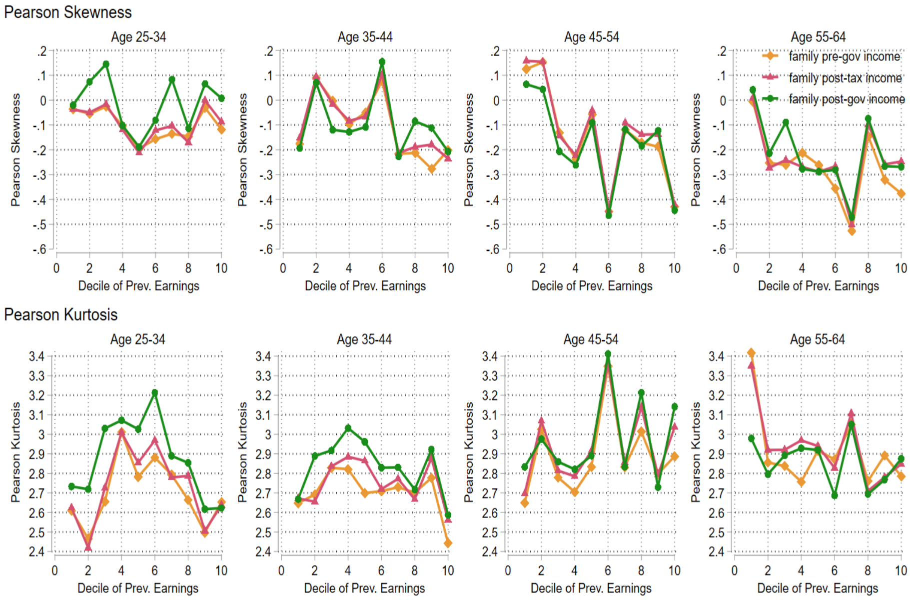

Figure F.38: Skewness and Kurtosis of the distribution of 3-year average changes of family income (P5-P95) at different levels. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

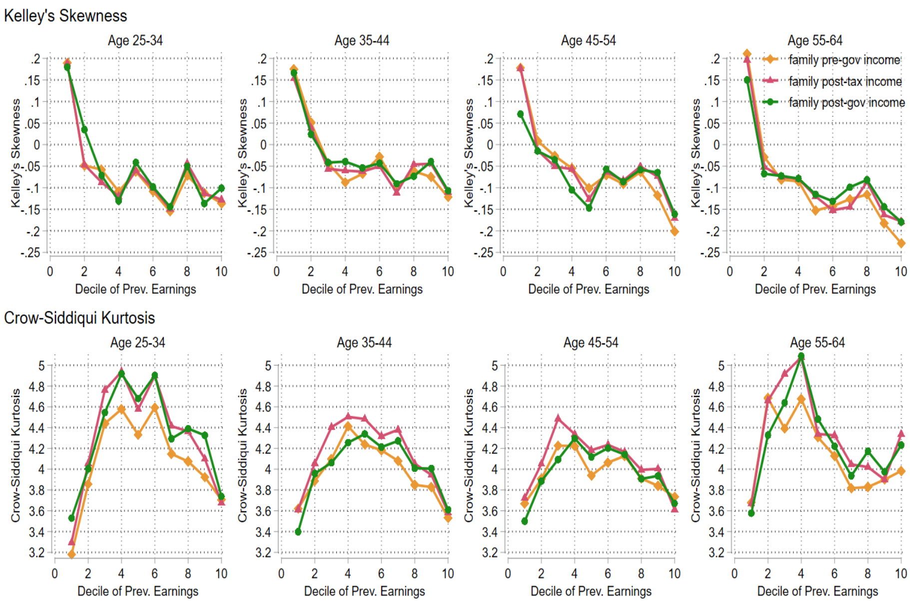

Figure F.39: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of annual changes of family income (P5-P95) at different levels. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

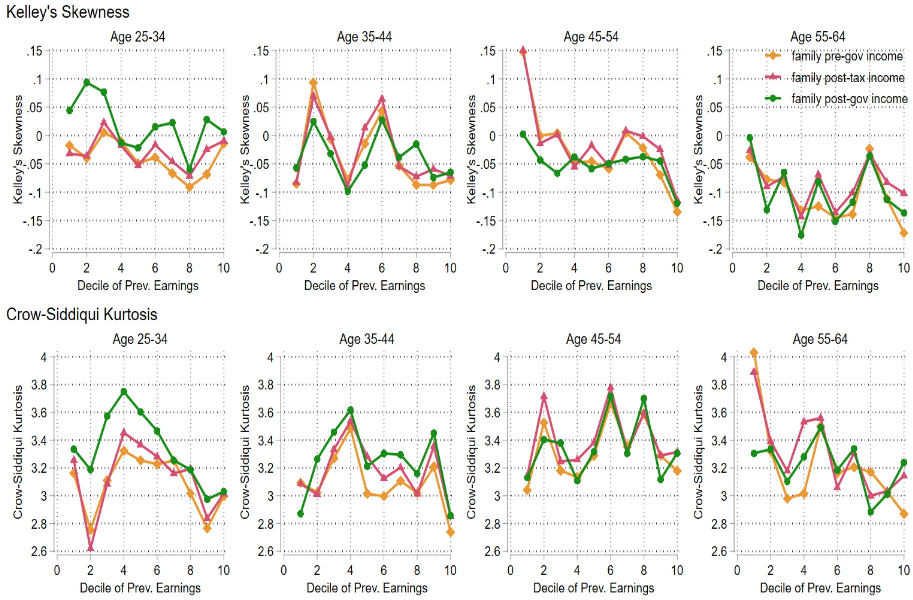

Figure F.40: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of 3-year average changes of family income (P5-P95) at different levels. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

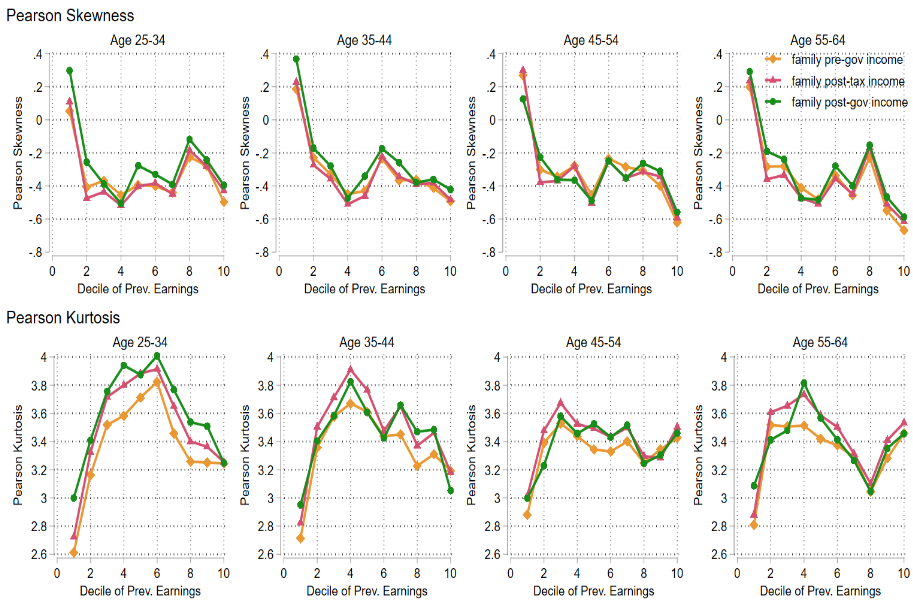

Figure F.41: Skewness and Kurtosis of the distribution of annual changes of family income (P5-P95) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

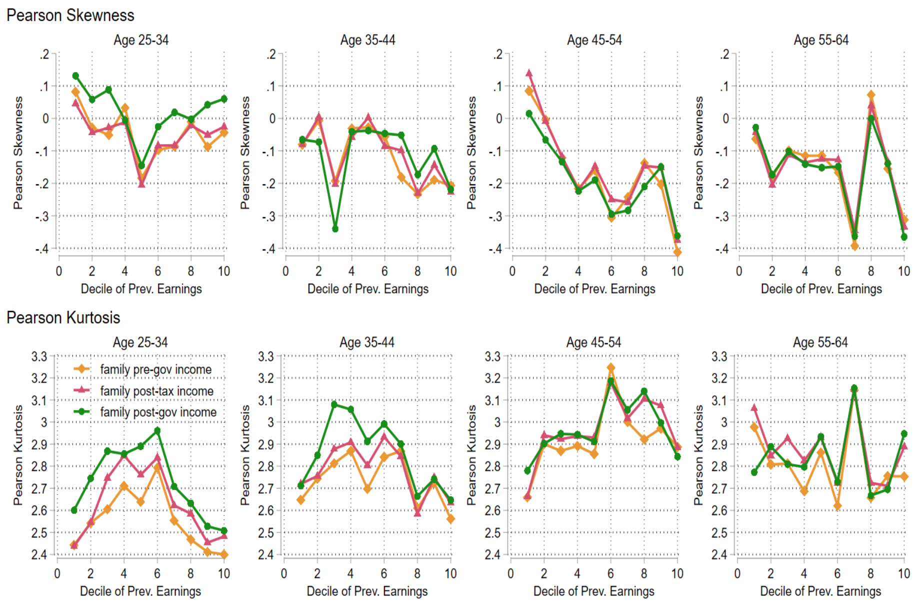

Figure F.42: Skewness and Kurtosis of the distribution of 3-year average changes of family income (P5-P95) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

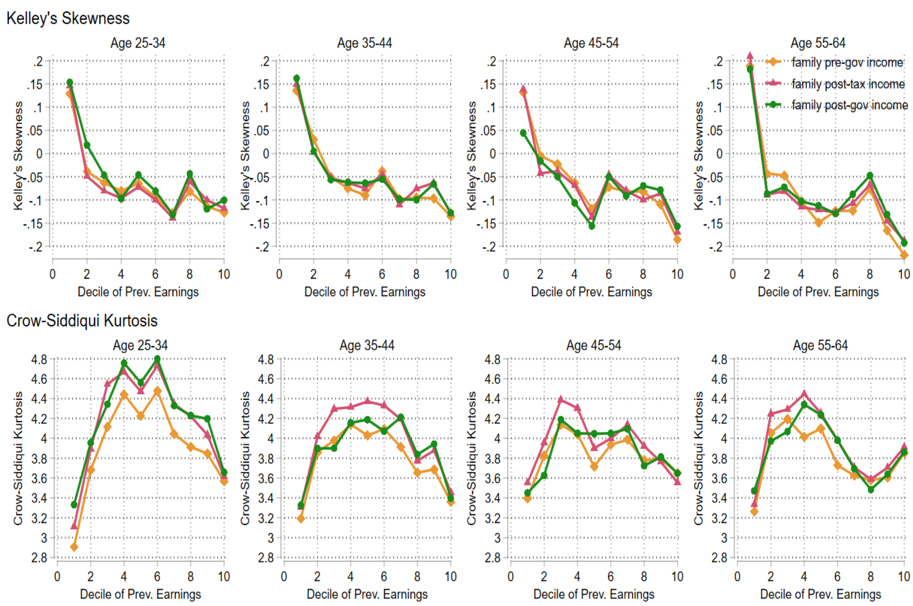

Figure F.43: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of annual changes of family income (P5-P95) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

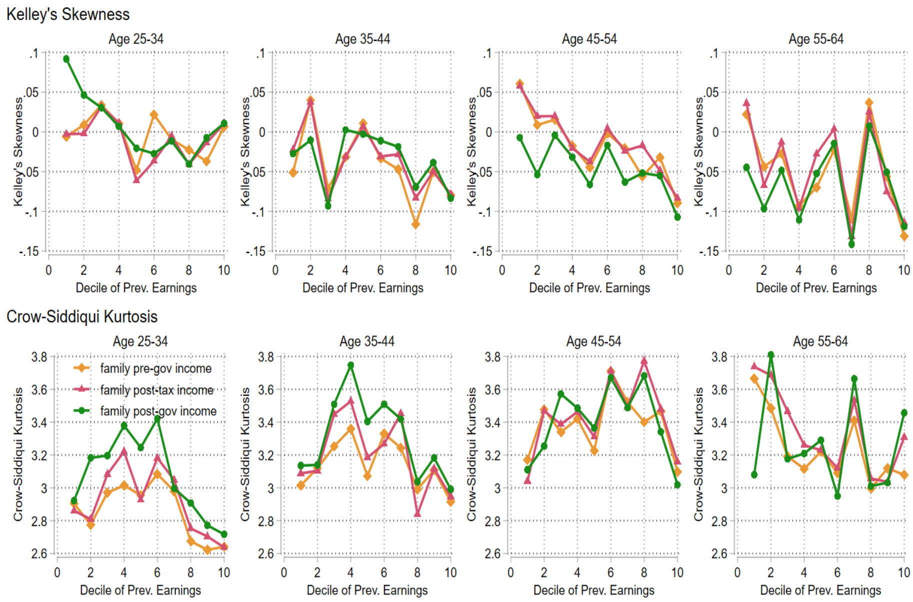

Figure F.44: Kelley's Skewness and Crow-Siddiqui Kurtosis of the distribution of 3-year average changes of family income (P5-P95) at different levels calculated via *Arc-Percent Change method*. The figure captures the relative contribution of tax and transfer to the third- and fourth-order risks of disposable family income.

F.4 Empirical distributions of shocks and their KDEs

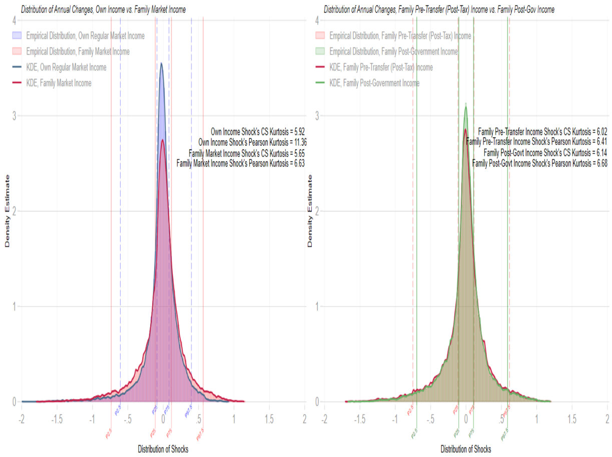

Figure F.45: Comparison of empirical distributions of annual shocks: individual market income vs. family market income (left panel), and family pre-transfer (post-tax) income vs. family post-government income (right panel).

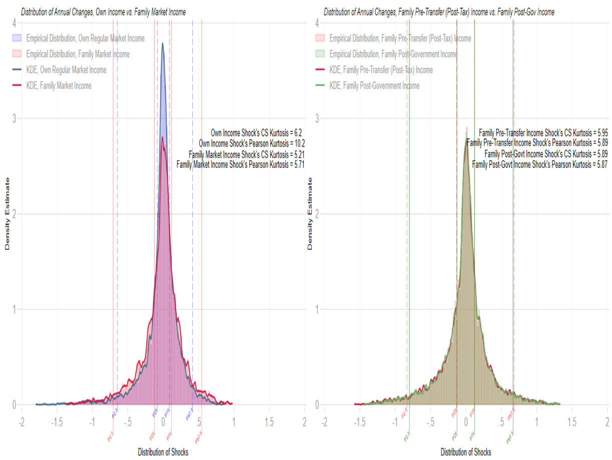

Figure F.46: Comparison of empirical distributions of annual shocks of the working-age cohort aged 55-64: individual market income vs. family market income (left panel), and family pre-transfer (post-tax) income vs. family post-government income (right panel).

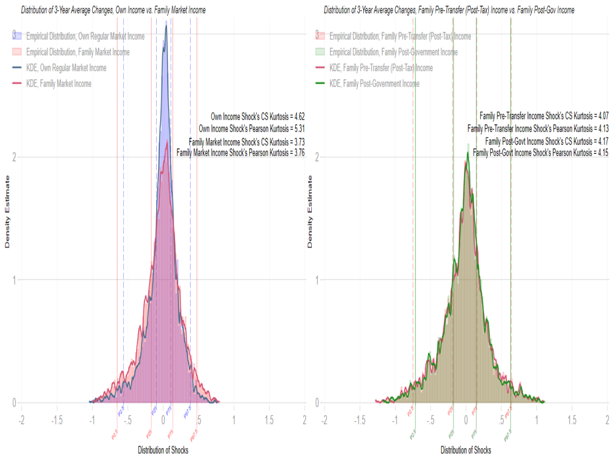

Figure F.47: Comparison of empirical distributions of 3-year average shocks of the working-age cohort aged 55-64: individual market income vs. family market income (left panel), and family pre-transfer (post-tax) income vs. family post-government income (right panel).

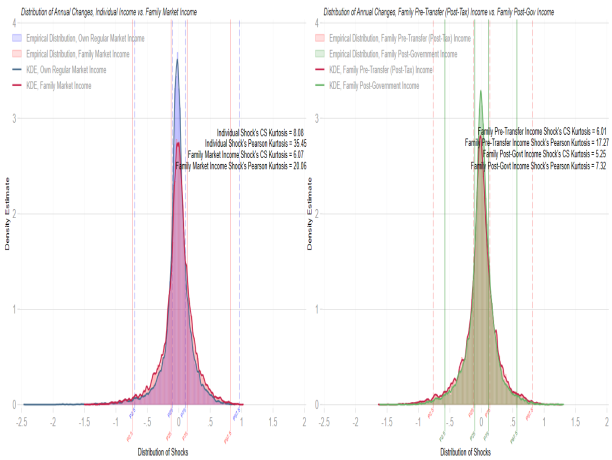

Figure F.48: Comparison of empirical distributions of anual average shocks of lower and upper middle income parents (decile 3 to decile 8): individual market income vs. family market income (left panel), and family pre-transfer (post-tax) income vs. family post-government income (right panel).

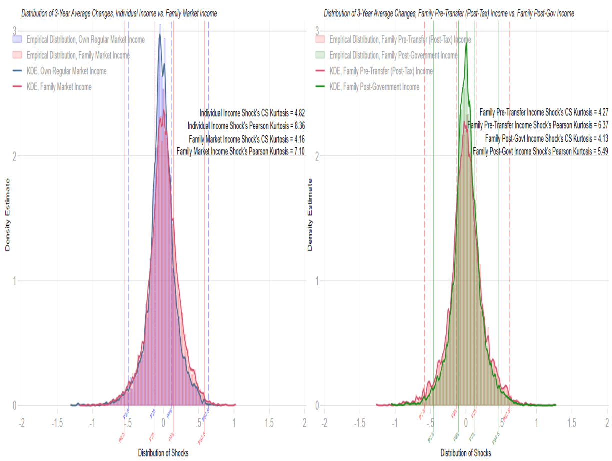

Figure F.49: Comparison of empirical distributions of 3-year average shocks of lower and upper middle income parents (decile 3 to decile 8): individual market income vs. family market income (left panel), and family pre-transfer (post-tax) income vs. family post-government income (right panel).

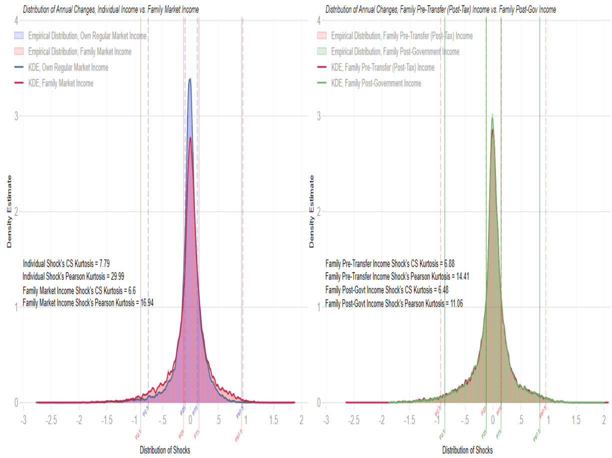

Figure F.50: Comparison of empirical distributions of anual average shocks of lower and upper middle income non-parents (decile 3 to decile 8): individual market income vs. family market income (left panel), and family pre-transfer (post-tax) income vs. family post-government income (right panel).

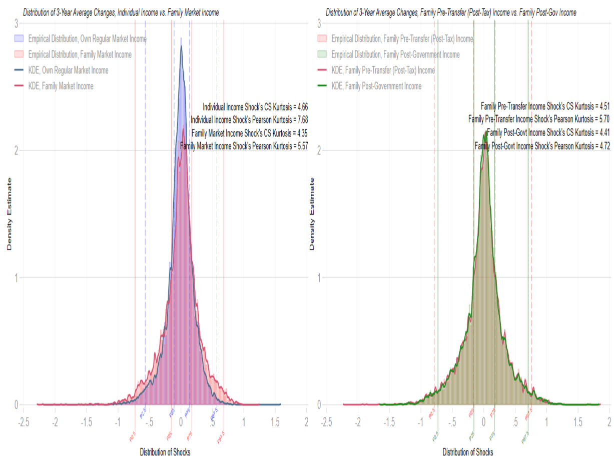

Figure F.51: Comparison of empirical distributions of 3-year average shocks of lower and upper middle income non-parents (decile 3 to decile 8): individual market income vs. family market income (left panel), and family pre-transfer (post-tax) income vs. family post-government income (right panel).

F.5 Higher-order moments: Male vs. female

P1-P99

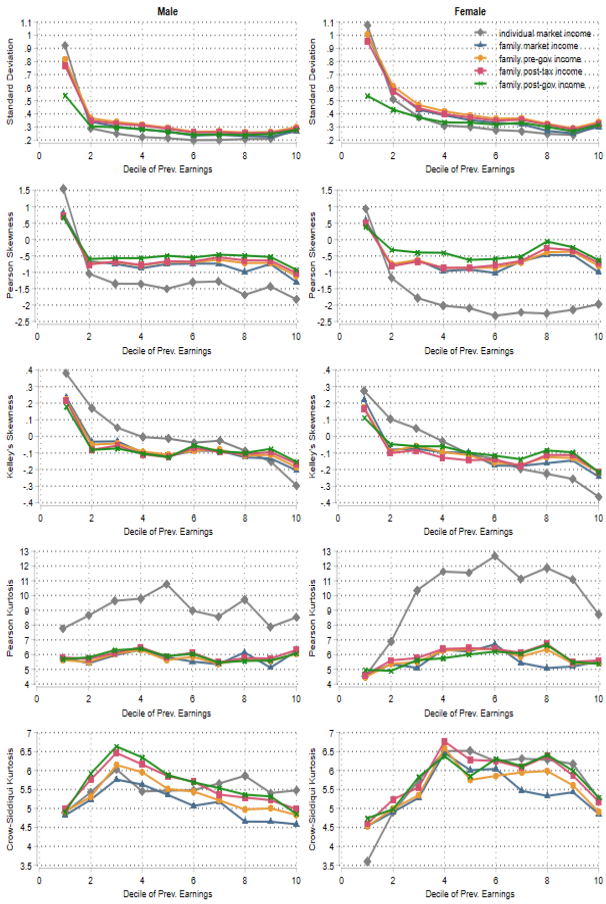

Figure F.52: Second- and higher-order moments of the distributions of annual income shocks (P1-P99) of male (left panel) and female (right panel) primary earners.

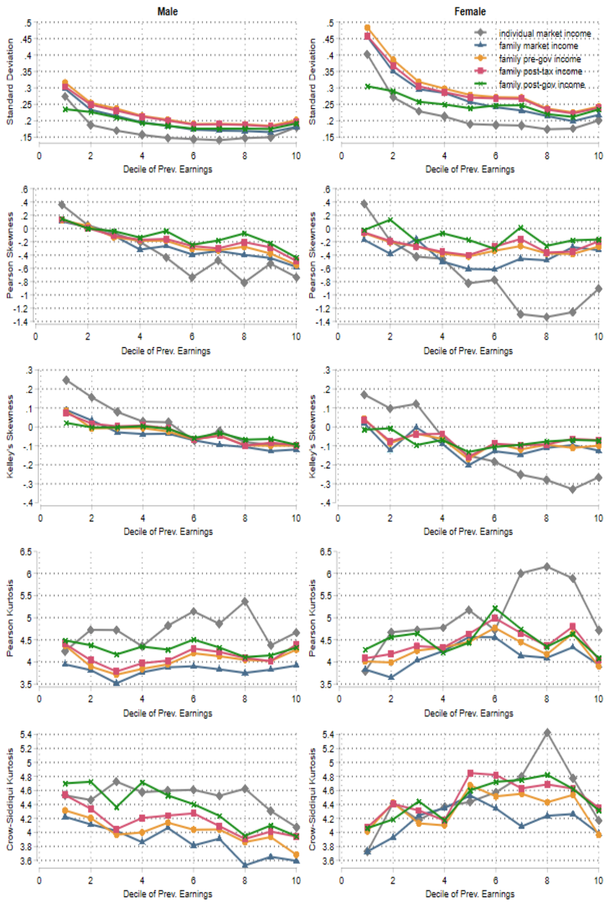

Figure F.53: Second- and higher-order moments of the distributions of 3-year average income shocks (P1-P99) of male (left panel) and female (right panel) primary earners.

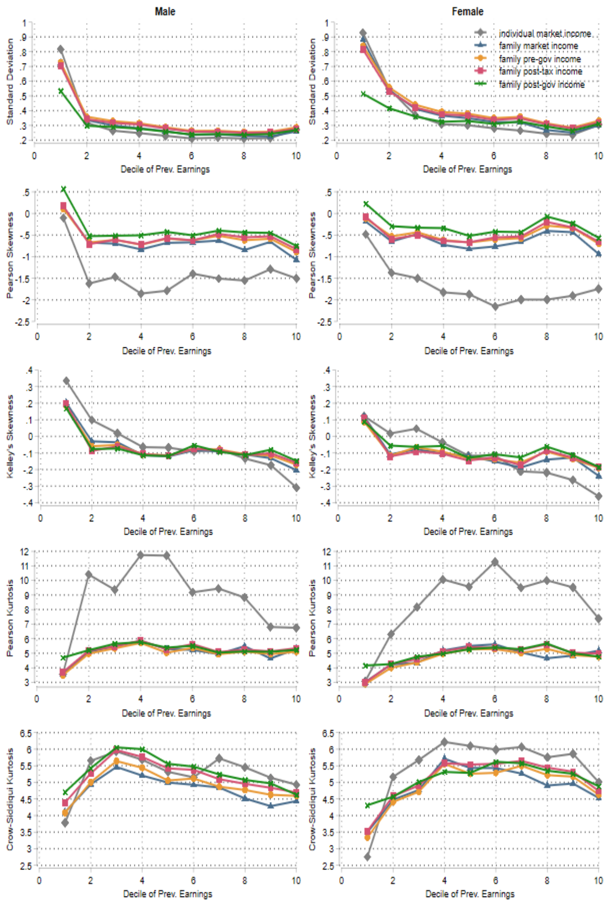

Figure F.54: Second- and higher-order moments of the distributions of annual income shocks (P1-P99) of male (left panel) and female (right panel) primary earners calculated via *Arc-Percent Change method*.

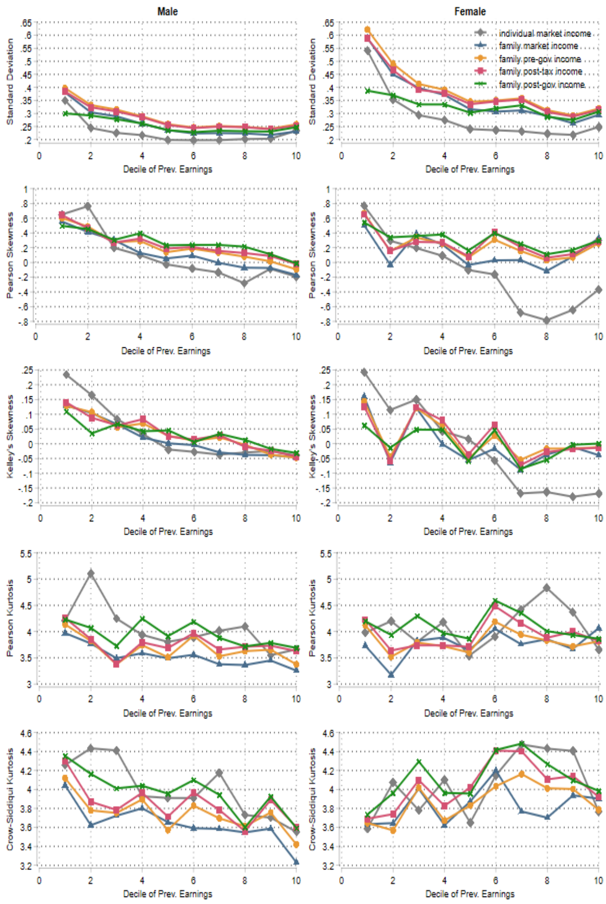

Figure F.55: Second- and higher-order moments of the distributions of annual income shocks (P1-P99) of male (left panel) and female (right panel) primary earners calculated via *Arc-Percent Change method.*

P5-P95

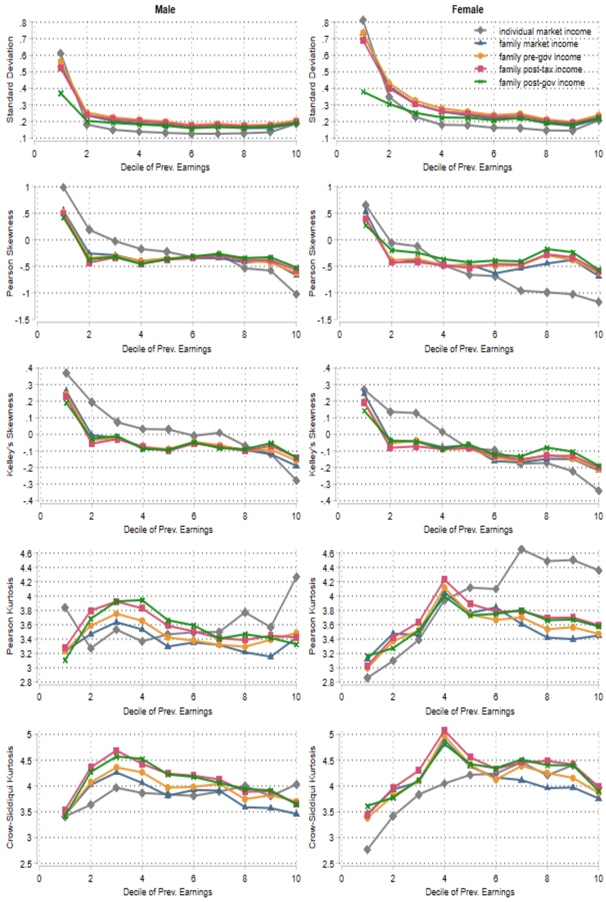

Figure F.56: Second- and higher-order moments of the distributions of annual income shocks (P5-P95) of male (left panel) and female (right panel) primary earners.

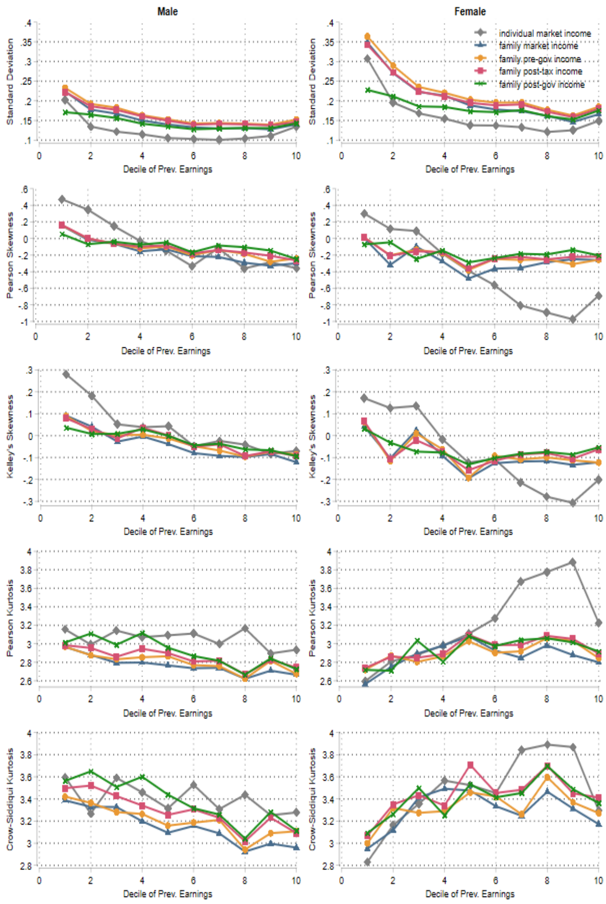

Figure F.57: Second- and higher-order moments of the distributions of 3-year average income shocks (P5-P95) of male (left panel) and female (right panel) primary earners.

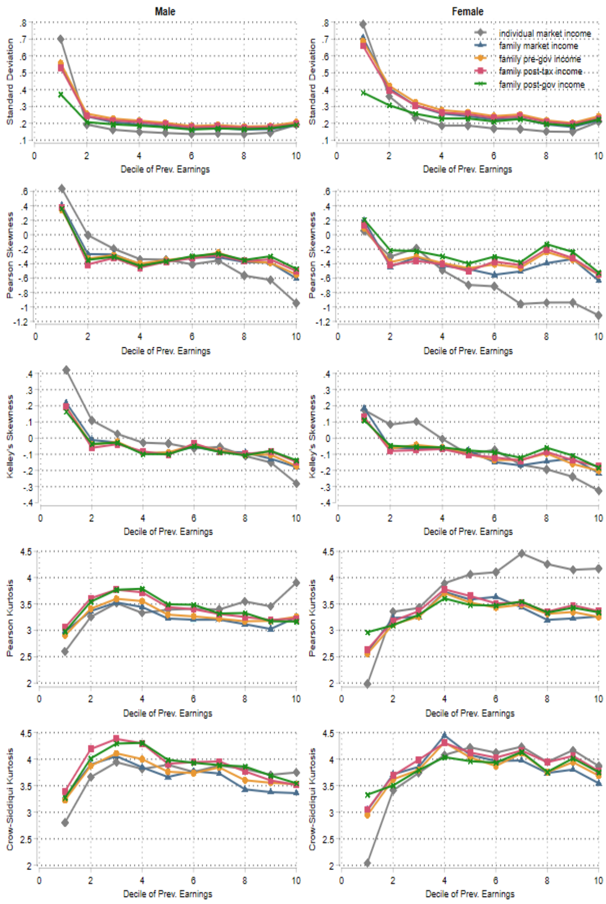

Figure F.58: Second- and higher-order moments of the distributions of annual income shocks (P5-P95) of male (left panel) and female (right panel) primary earners calculated via *Arc-Percent Change method*.

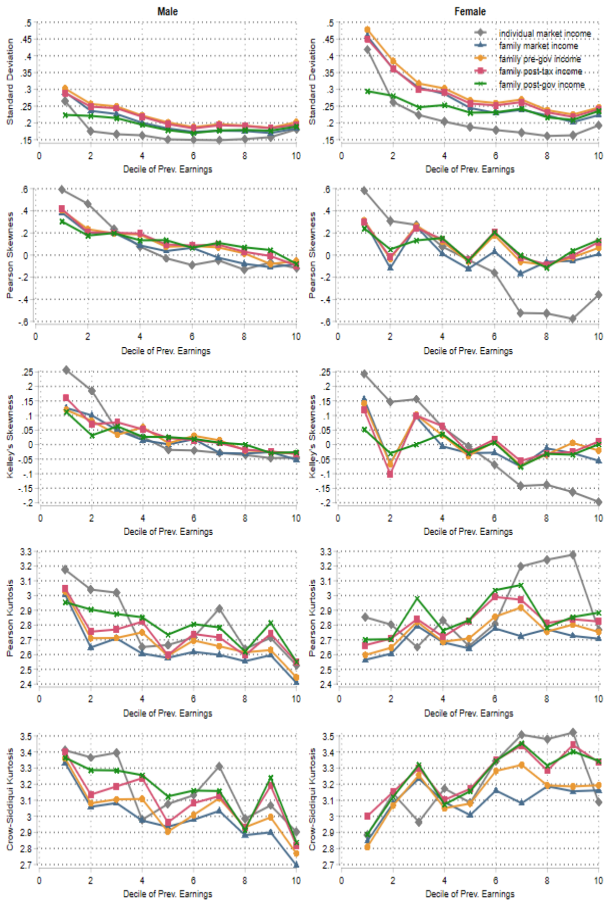

Figure F.59: Second- and higher-order moments of the distributions of annual income shocks (P5-P95) of male (left panel) and female (right panel) primary earners calculated via *Arc-Percent Change method*.

F.6 Higher-order moments: Parent vs. non-parent

Non-robust

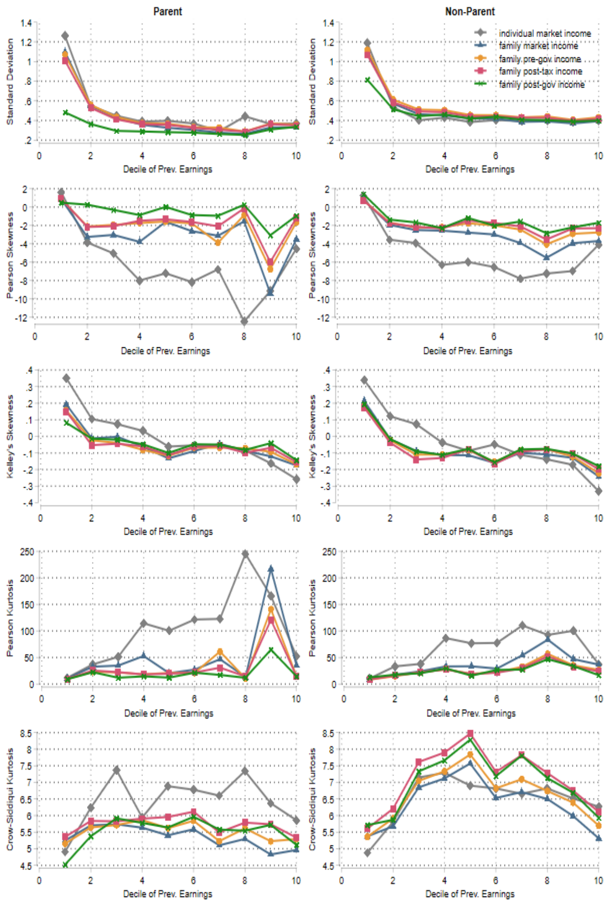

Figure F.60: Non-robust second- and higher-order moments of the distributions of annual income shocks of parent (left panel) and non-parent (right panel) primary earners.

P1-P99

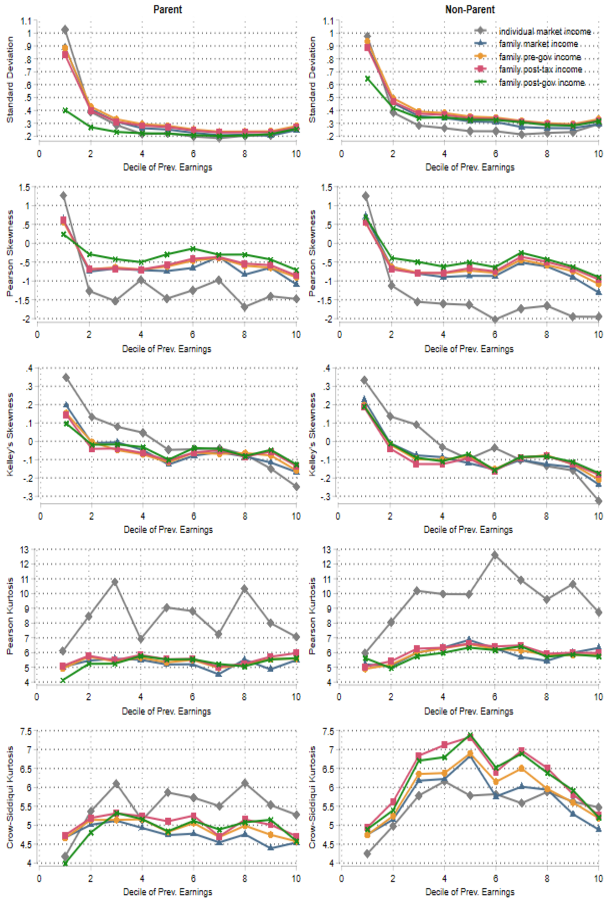

Figure F.61: Second- and higher-order moments of the distributions of annual income shocks (P1-P99) of parent (left panel) and non-parent (right panel) primary earners.

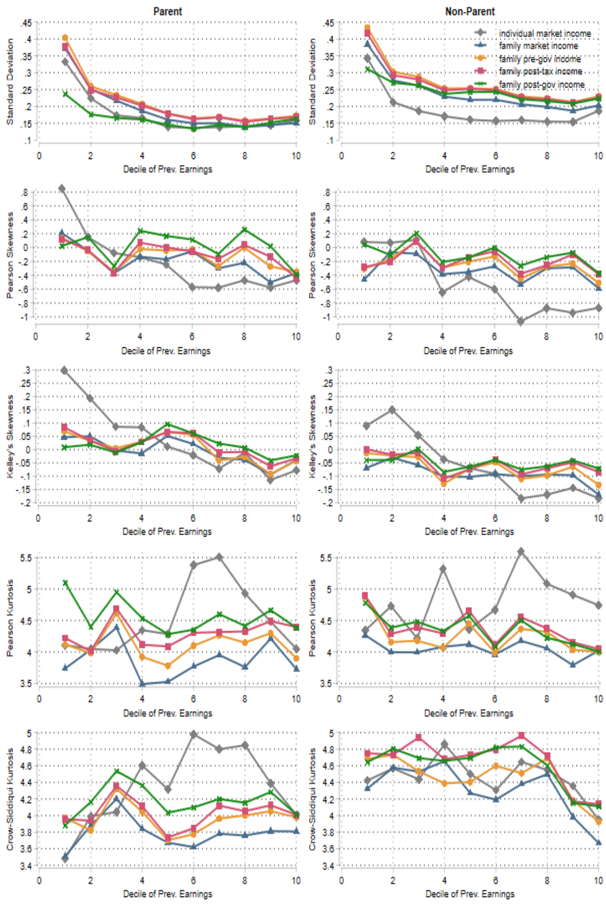

Figure F.62: Second- and higher-order moments of the distributions of 3-year average income shocks (P1-P99) of parent (left panel) and non-parent (right panel) primary earners.

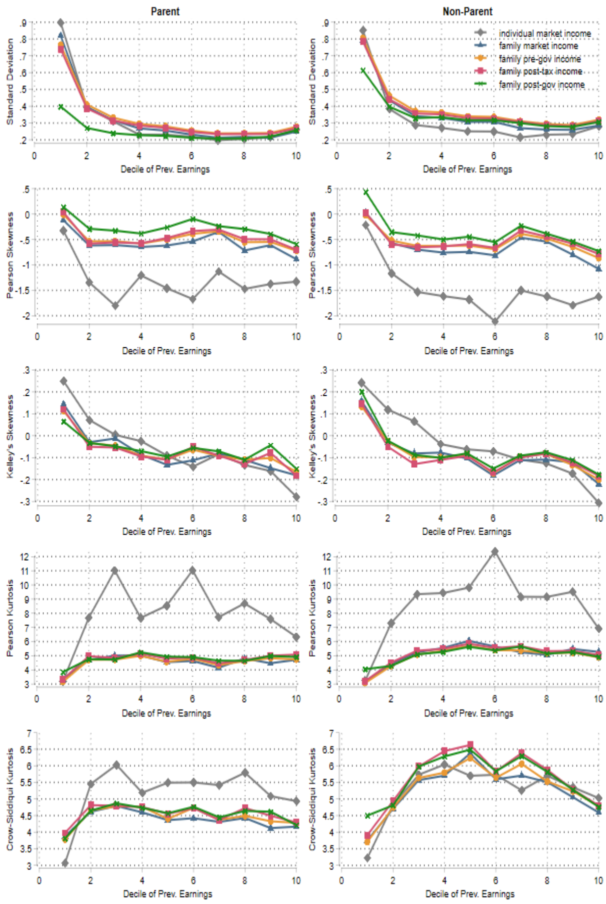

Figure F.63: Second- and higher-order moments of the distributions of annual income shocks (P1-P99) of parent (left panel) and non-parent (right panel) primary earners calculated via *Arc-Percent Change method*.

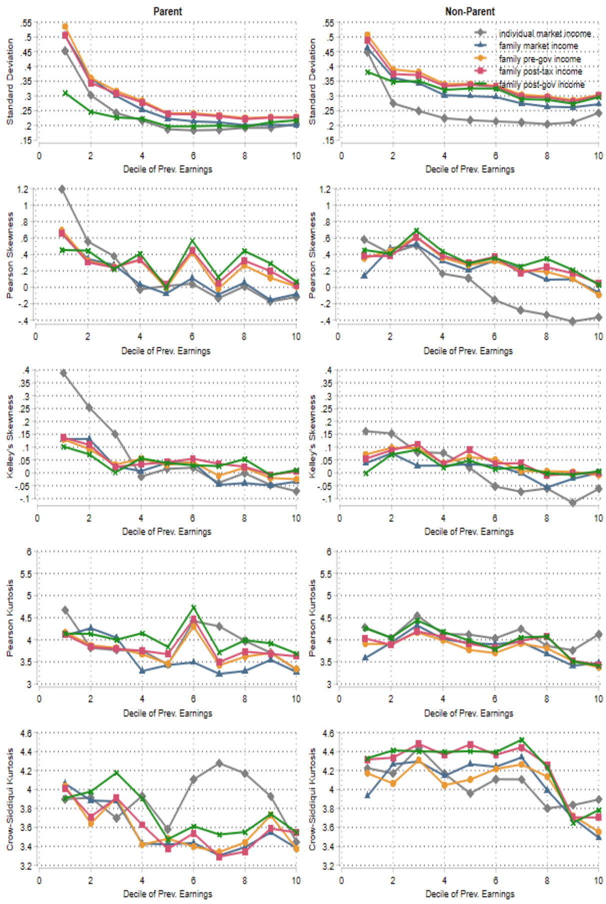

Figure F.64: Second- and higher-order moments of the distributions of annual income shocks (P1-P99) of parent (left panel) and non-parent (right panel) primary earners calculated via *Arc-Percent Change method*.

P5-P95

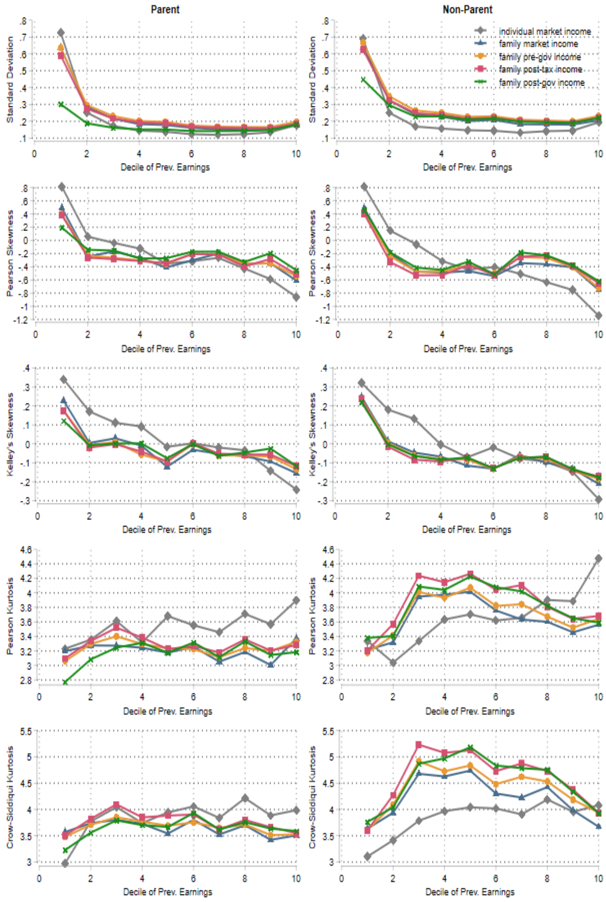

Figure F.65: Second- and higher-order moments of the distributions of annual income shocks (P5-P95) of parent (left panel) and non-parent (right panel) primary earners.

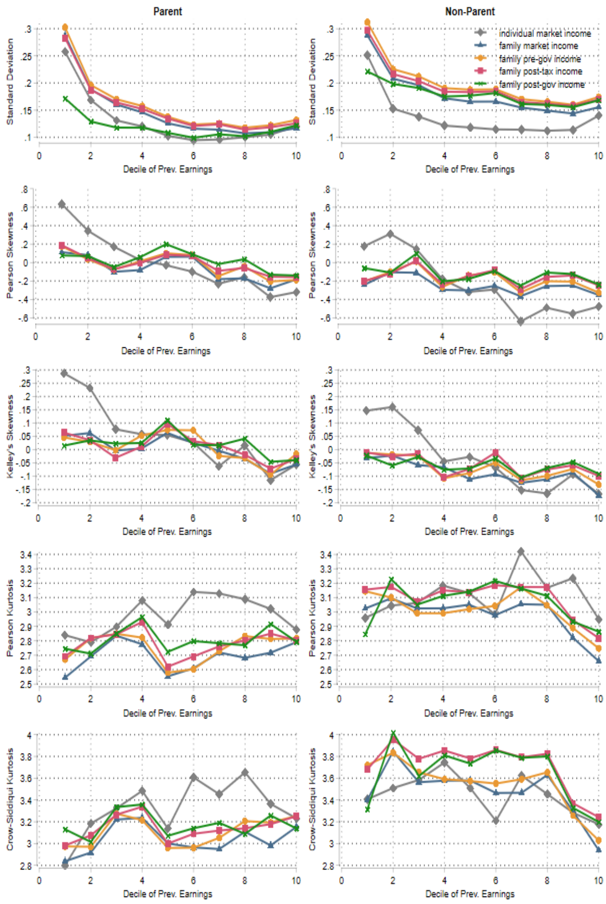

Figure F.66: Second- and higher-order moments of the distributions of 3-year average income shocks (P5-P95) of parent (left panel) and non-parent (right panel) primary earners.

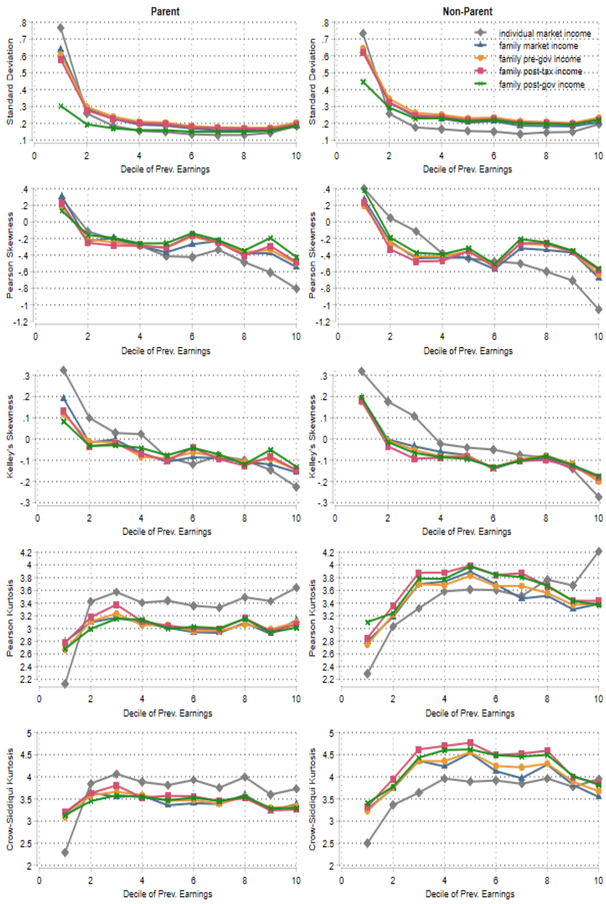

Figure F.67: Second- and higher-order moments of the distributions of annual income shocks (P5-P95) of parent (left panel) and non-parent (right panel) primary earners calculated via *Arc-Percent Change method*.

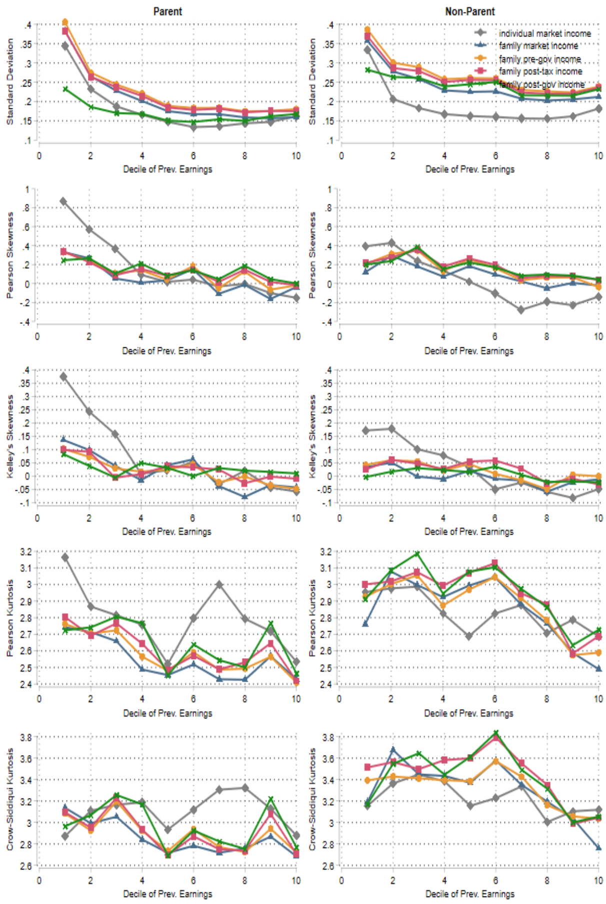

Figure F.68: Second- and higher-order moments of the distributions of annual income shocks (P5-P95) of parent (left panel) and non-parent (right panel) primary earners calculated via *Arc-Percent Change method*.

F.7 Higher-order moments: Partnered vs. lone parents

P1-P99

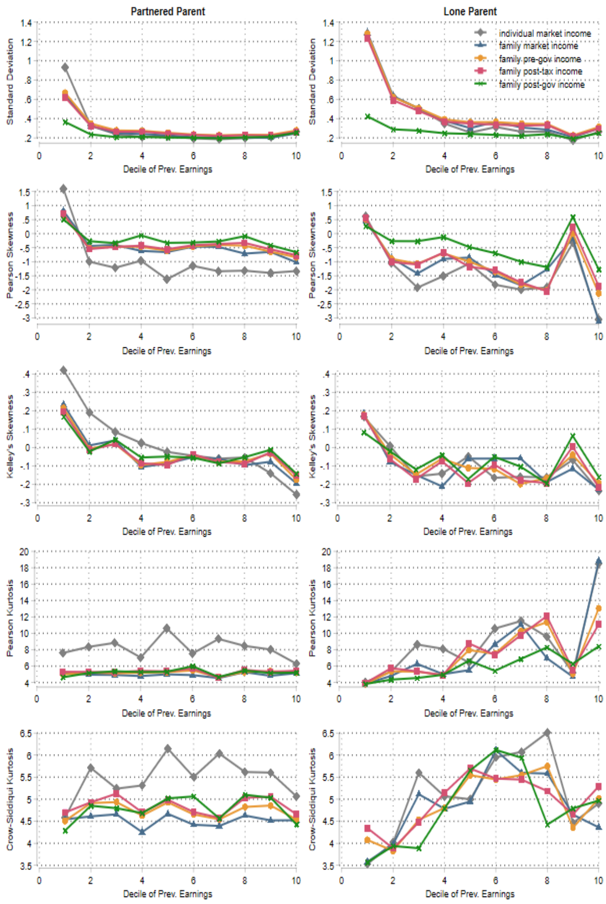

Figure F.69: Second- and higher-order moments of the distributions of annual income shocks (P1-P99) of partnered parent (left panel) and lone parent (right panel) primary earners.

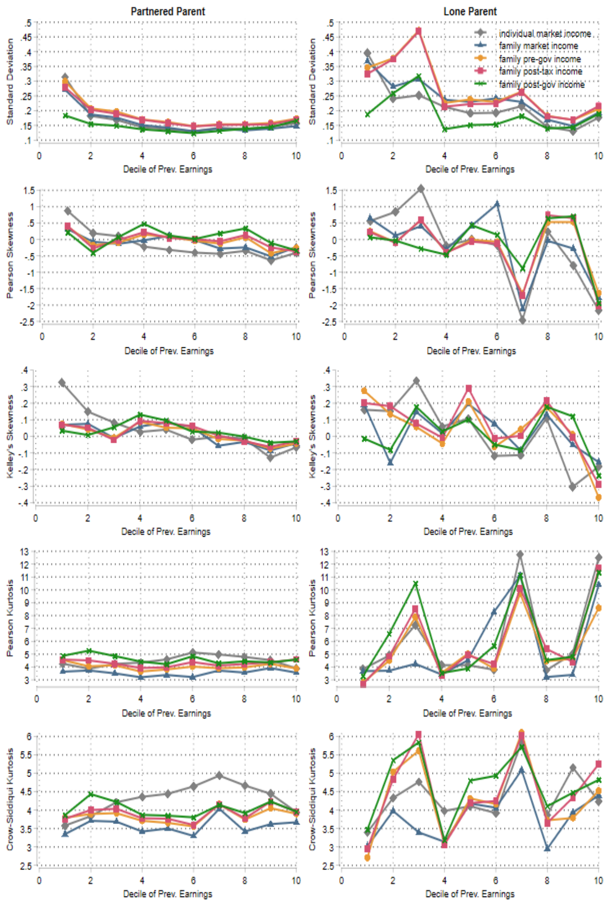

Figure F.70: Second- and higher-order moments of the distributions of 3-year average income shocks (P1-P99) of partnered parent (left panel) and lone parent (right panel) primary earners.

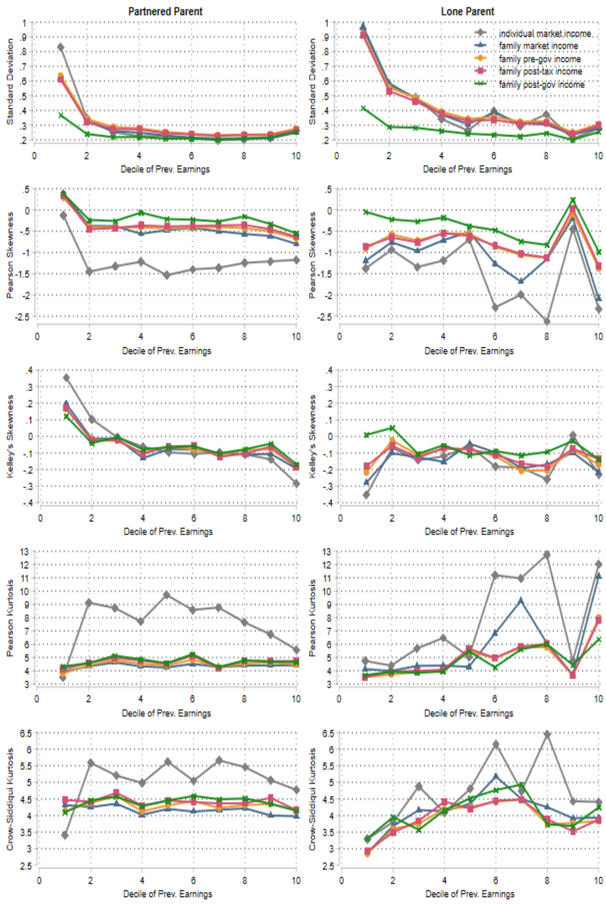

Figure F.71: Second- and higher-order moment of the distributions of annual income shocks (P1-P99) of partnered parent (left panel) and lone parent (right panel) primary earners calculated via *Arc-Percent Change method*.

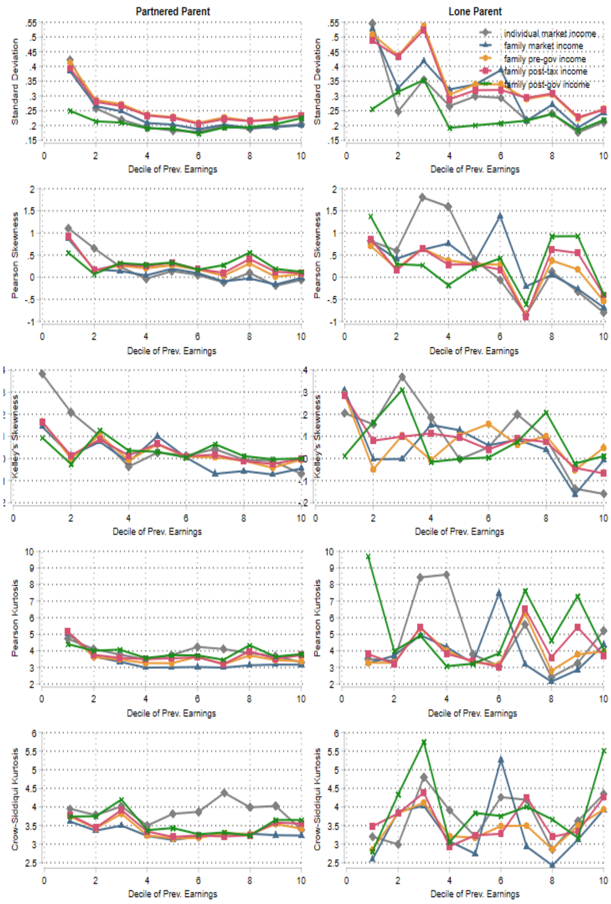

Figure F.72: Second- and higher-order moments of the distributions of annual income shocks (P1-P99) of partnered parent (left panel) and lone parent (right panel) primary earners calculated via *Arc-Percent Change method*.

P5-P95

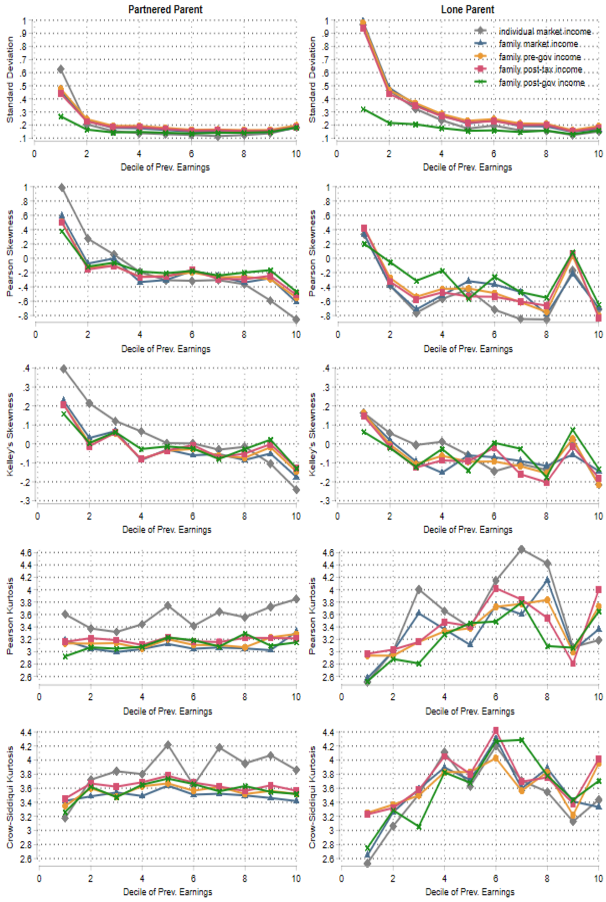

Figure F.73: Second- and higher-order moments of the distributions of annual income shocks (P5-P95) of partnered parent (left panel) and lone parent (right panel) primary earners.

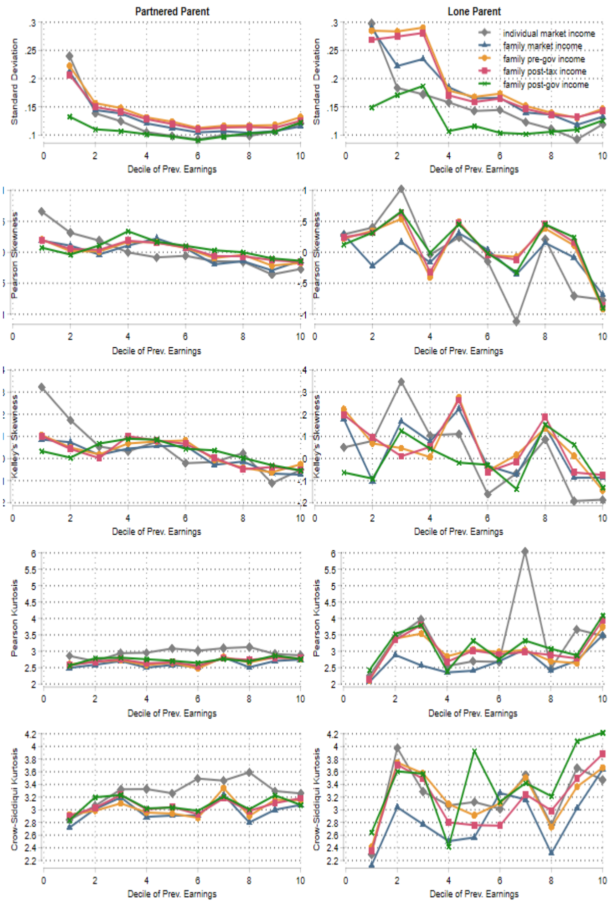

Figure F.74: Second- and higher-order moments of the distributions of 3-year average income shocks (P5-P95) of partnered parent (left panel) and lone parent (right panel) primary earners.

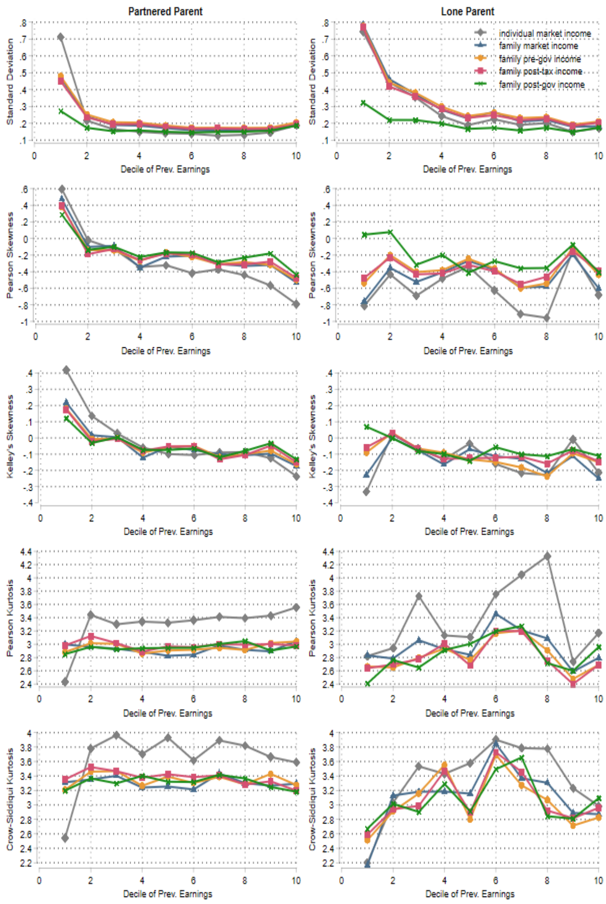

Figure F.75: Second- and higher-order moments of the distributions of annual income shocks (P5-P95) of partnered parent (left panel) and lone parent (right panel) primary earners calculated via *Arc-Percent Change method*.

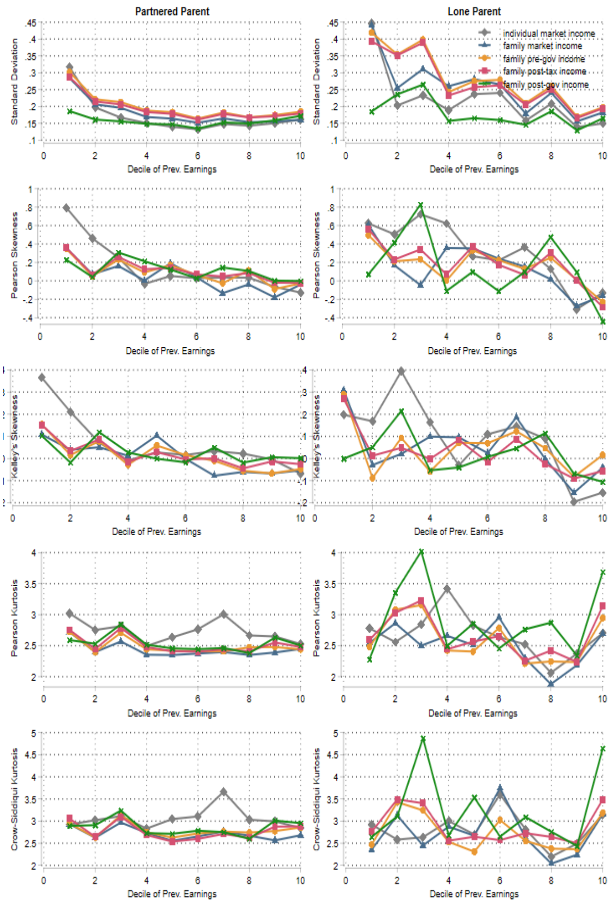

Figure F.76: Second- and higher-order moments of the distributions of annual income shocks (P5-P95) of partnered parent (left panel) and lone parent (right panel) primary earners calculated via *Arc-Percent Change method*.

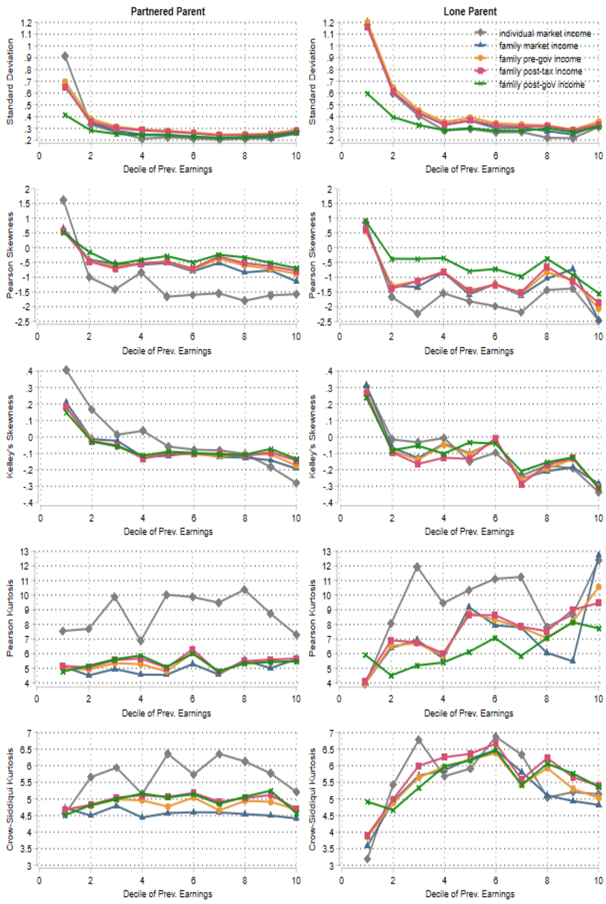

Figure F.77: Second- and higher-order moments of the distributions of annual income shocks of partnered parent (left panel) and lone parent (right panel) primary earners (P11-P99) Pearson statistics.