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Mario Giarda
Ignacio Rojas
Sergio Salgado

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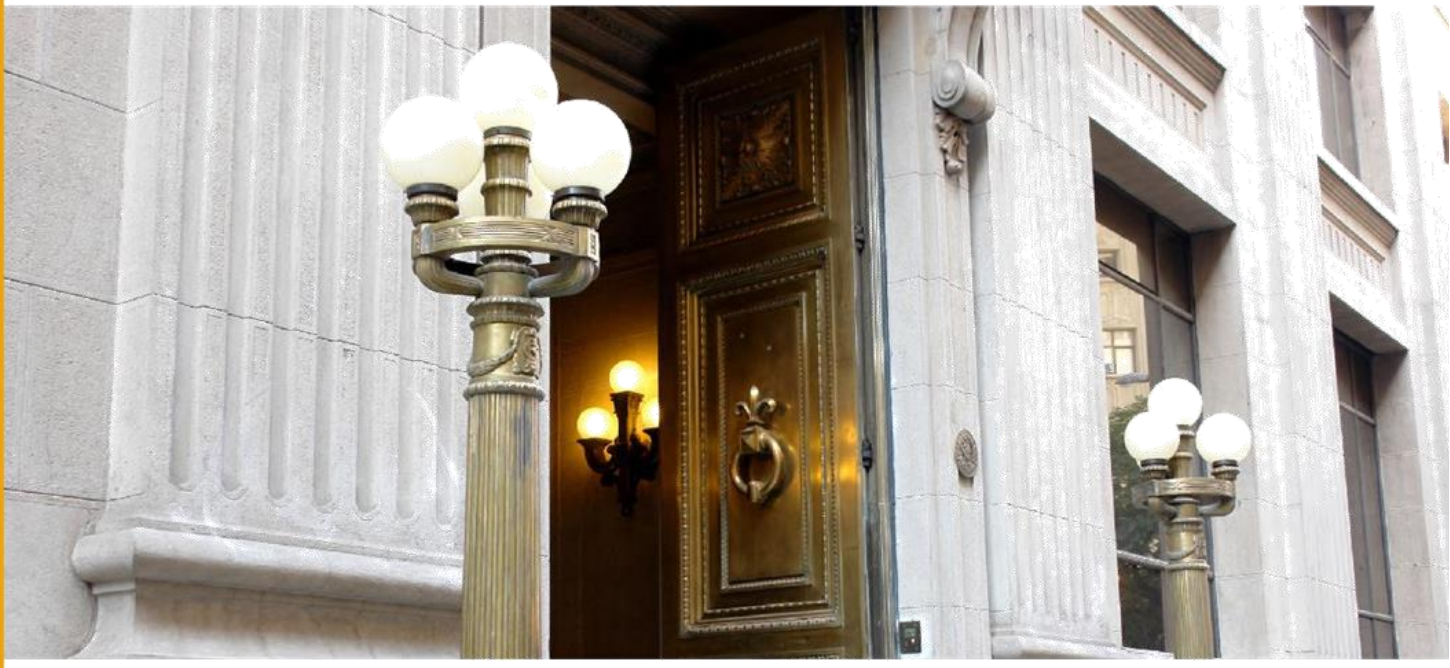

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Agustinas 1180, Santiago, Chile
Teléfono: (56-2) 3882475; Fax: (56-2) 38822311

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Characterizing Income Risk in Chile and the Role of Labor Market Flows*

Mario Giarda† Ignacio Rojas‡ Sergio Salgado§

Resumen

Este trabajo caracteriza la dinámica del ingreso en Chile, una economía pequeña y abierta de rápido crecimiento, utilizando 21 años de datos administrativos de alta calidad sobre remuneraciones laborales para la población de trabajadores formales. Encontramos una disminución significativa en la desigualdad de ingresos hasta el percentil 90 de la distribución. Durante el mismo período, aumentó la volatilidad del ingreso y la asimetría del crecimiento salarial se volvió negativa, especialmente después de la recesión por COVID-19. Usando datos mensuales de remuneraciones, mostramos que, más que el riesgo de desempleo, son las fluctuaciones salariales dentro de una relación laboral y en las transiciones entre empleadores las que contribuyen principalmente a la asimetría negativa del crecimiento de las remuneraciones que típicamente se observa en una recesión.

Abstract

This paper characterizes the income dynamics of Chile, a fast-growing small-open economy, using 21 years of high-quality administrative data of labor earnings for the population of formal workers. We find a significant decline in income inequality up to the 90th percentile of the distribution. During the same period, income volatility increased, and the skewness of earnings growth became negative, especially after the COVID recession, indicating a shift in the sources of workers' earnings risk. Using monthly earnings data, we show that rather than unemployment risk, it is earnings fluctuations that occur within an employment relation and in transitions between employers that are the major contributor to the negative skewness of earnings growth that is typically observed in a recession.

*The views expressed are those of the author and do not necessarily reflect the views of the Central Bank of Chile or its board members. This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities by virtue of collaboration agreements signed with these institutions.To secure the privacy of workers and firms, the CBC mandates that the development, extraction, and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. All the analysis was implemented by the authors and did not involve or compromise the Servicio de Impuestos Internos de Chile (SII), Civil Registry nor Administrador de Fondos de Cesant´ıa. The information contained in the databases of the SII is of a tax nature originating in self-declarations of taxpayers presented to the SII; therefore, the veracity of the data is not the responsibility of the SII. We thank Paula Araya for her superb research assistance.

†Central Bank of Chile; mgiarda@bcentral.cl
‡University of Minnesota; rojas283@umn.edu
§The Wharton School, University of Pennsylvania; ssalgado@wharton.upenn.edu

1 Introduction

There is ample empirical evidence of the income dynamics of workers in developed countries (Guvenen et al., 2021). However, workers' income dynamics in fast-growing, small open economies are less well-known. To fill this gap, this paper describes the evolution of the distribution of income (inequality) and the distribution of earnings growth (income volatility) in Chile, following the methods and analysis described by Guvenen et al. (2022). We add evidence from this small open economy to the growing evidence of inequality and income risk evolution over time and the business cycle.

In this paper, we use high-quality administrative records collected by the Internal Revenue Service that comprise the universe of formal workers in the private sector and government institutions. This dataset is an employer-employee monthly panel that allows researchers to match the characteristics of firms and workers at a firm-individual level. In the first part of the paper, however, we follow the bulk of the literature and add a particular individual's labor earnings sources within a calendar year to obtain their annual salary and wages. In the second part of the paper, we extend the annual measures and show results for income inequality and income risk at a business cycle frequency by using monthly data. In that case, we show the evolution of income risk and the sources of it analyzing the moments of the income change distribution conditional on labor market flows.

We show that Chile shares several features of inequality and income risk with other developing economies like Brazil and Mexico in that i) Chile displays high inequality among both men and women, ii) has experienced a decline in inequality over the past two decades, and iii) younger cohorts seem to have lower inequality overall. Chilean workers also have highly volatile income growth but positive skewness and high average income growth over the period under analysis.

Chile experienced two phases of growth over the two decades we analyzed: a fast phase between 1997 and 2012, in which GDP per capita grew by about 3% yearly, and then a slow phase between 2013 and 2023, in which growth was a disappointing 0.8%. We show that this change in trend GDP is likely due to a slowdown in productivity growth. We analyze the impact of macroeconomic performance on inequality and income risk.

First, we find that during the period of strong GDP growth, income inequality declined at the bottom of the distribution; this is, low-income workers benefited the most from the rapid growth relative to high-income workers. For instance, among males, the 10th percentile of income distribution grew by 50% between 2004 and 2013. In contrast, the 90th percentile only grew by 30%, driving a significant decline in earnings inequality—as measured by the 90th-to-10th earnings percentile differential. This rapid decline in inequality halted after 2013 and has remained stable since then. Interestingly, the picture differs for women, who experienced a decline in earnings inequality only after 2013, a period of slower economic growth.

Second, although income inequality at the bottom 90th percentile declined in Chile during the last 20 years, top income inequality has also decreased significantly, especially after 2013. In fact, between 2004 and 2013, the 90th and 99th percentiles grew almost at the same pace for all groups, men and women, experiencing an increase of about 35%. After 2013, however, the 99th to 90th differential declined for men and remain stable for women.

We also find that income risk is greatly affected by the changes in aggregate growth. Over the decades we have analyzed, we find that the dispersion of income growth distribution increased significantly, with a big increase during the COVID-19 pandemic. In constrast, the skewness of earnings growth—a measure of labor earnings downside risk—has declined, especially since 2014, when the slow growth phase kicked in more strongly. These facts are important findings since they confirm that aggregate economic growth translates into more substantial income growth and lower income risk. The latter may affect consumption-savings decisions, interest rates, and other phenomena.

Besides these general patterns, we provide several additional moments of the income and earnings growth distribution, within and across generations, and different measures of income mobility. We hope these moments add to the growing characterization of the income distribution in Chile using administrative data (Aldunate et al., 2020; Albagli et al., 2022, 2023). Our results—available for public use on the GRID's website— can help researchers calibrate heterogeneous agent models of the Chilean economy and small open economies in general.

In the second part of the paper, we extend our analysis and consider labor income risk at higher frequencies. In particular, we use monthly earnings to show that at a higher frequency, the cyclicality of labor income risk is also present. Moreover, we split these results by labor market flows, considering transitions between employment and unemployment, employment-to-employment, and people who stay in their employment relationship (stayers). Perhaps surprisingly, we find that the main contributors to the aggregate cyclicality of income risk, as measured by the skewness of earnings growth, come from the stayers—i.e., people who remain in their jobs—rather than individuals who move into unemployment or switch jobs. In particular, it is the stayers who, in recessions, face a stronger left-tail risk coming from a lower probability of getting a wage raise. The second major contributor to the aggregate cyclicality of skewness comes from employment-to-employment transition, in this case, comes from an decline in the chances of getting a significant rise in earnings when switching jobs. This means that unemployment is not the only source of income risk fluctuations, and is a minor contributor to the cyclicality in the skewness of earnings growth typically observed during recessions.

The rest of the paper is organized as follows. Section 2 describes the institutional background and the data we use; section 3 discusses the results for income inequality and its evolution; section 4 studies the distribution of income growth, volatility and income risk; section 5 studies the distribution of income growth, volatility and income risk conditional on labor market flows with monthly data. Finally, section 6 concludes.

2 Institutional Background and Data

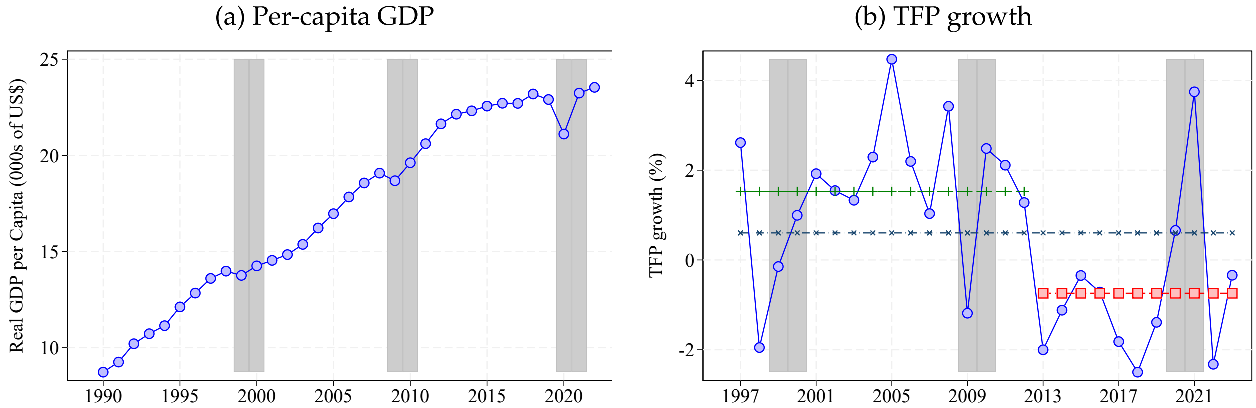
2.1 Institutional and Historical Background

Chile is a Latin American country that has experienced fast growth over the past three decades. We can observe this by the remarkable per capita GDP growth, which averaged 3% annually in 1991-2023 (see Figure 1a). These growth rates were accompanied by a strong growth in formal labor force participation, which increased from about 52 to 59% between 1990-2019, with a sharp decline back to 56% after the COVID-19 pandemic, a strong growth in real wages of about 60%, and a strong growth in female labor force participation (see Figure OA.1b). A more striking figure is the sharp decline in the poverty rate from about 68.5% in 1990 to 8.6% in 2017[1]. Thus, in these dimensions, the economic performance of Chile has been a success both at a macroeconomic level and in socioeconomic terms. Responsible macroeconomic policies have contributed to economic stabilization, especially controlling inflation to low levels with respect to comparable countries over the period 1990-2023.

Regarding growth, we can separate these decades into two distinct phases. The *fast phase*, between 1990 and 2012, with an average per-capita GDP growth of rate 4% and a *slow phase*, between 2013-2023 with slower growth rates of about 0.8%. This significant change affected labor markets, as official wage figures show (see Figure OA.1a): The real wage grew fast until 2012 (at about 2.7% on average) and decelerated to 1.2% in the slow growth phase.

[1]See PNUD, 2019 (Evolución de la Pobreza 1990-2017: ¿como ha cambiado Chile?).

FIGURE 1: Evolution of per-capita GDP and TFP growth.



Notes: Figure 1 panel (a) shows the evolution of the GDP per-capita with the PPP correction. Panel (b) shows annual change of TFP. The dashed line represent the averages levels within the corresponding period-period 1997-2012 green crossed-line, period 2013-2023 red squared-line. The gray bars represent recession years, defined as years with an output gap of -0.5 percent or less.

A plausible explanation for this disappointing slow phase is the slowdown in total factor productivity (TFP) growth that Chile experienced in 2012. Figure 1b shows the evolution of the measures of Total Factor Productivity the Central Bank of Chile publishes (see Bauducco et al., 2024). We can see a dramatic fall in TFP growth starting in 2013. Over the fast phase (from 1997 to 2012), the average TFP growth was 1.5%, while in the slow phase, it fell to -0.7%. Possible explanations are the end of a commodity supercycle (not present before 2005) and global trends in productivity slowdown. As we will see below, a striking result is the quick effect this had over other variables like GDP growth and labor markets. Next, we analyze the effects of these aggregate dynamics on labor market outcomes, such as inequality and income risk.

2.2 Data Description

Our dataset consists of high-quality, anonymized administrative records covering the population of formal firm-employed workers in Chile from 2004 to 2024. These data are collected for administrative purposes, which reduces the measurement error and sample attrition commonly found in survey-based sources. We use information from form DJ1887, where firms report individual wages annually. This dataset is merged with the Civil Register to obtain demographic variables such as age and gender. All processing occurs on a blind server that enables secure merging and computation while safeguarding the privacy of individuals and firms. To ensure confidentiality, all estimates presented in this paper and those provided to the GRID project comply with a minimum

TABLE 1: Descriptive Statistics for Baseline Yearly Labor Earnings Sample. Period averages.

	Obs. (1000s)		Income		Age Distribution (%)		
Period	Female	Male	Female	Male	25-34	35-44	45-55
2004-2012	1,277	2,207	10,799	13,851	38.9%	34.6%	26.4%
2004-2007	1,064	2,000	10,096	12,512	39.8%	35.5%	24.5%
2008-2012	1,448	2,374	11,361	14,922	38.2%	33.8%	28.0%
2013-2024	1,909	2,694	15,088	18,924	36.2%	34.1%	29.5%
2013-2019	1,871	2,692	13,972	17,997	38.1%	32.7%	29.0%
2020-2024	1,963	2,696	16,651	20,221	33.6%	36.0%	30.2%

Notes: Table shows descriptive statistics of our baseline sample. Nominal values are deflated to 2018 prices using Chilean CPI and transformed to US dollars using 2018 average exchange rate. Each statistic was obtained with more than 30 individuals.

cell size of 30 individuals. Combined with the large sample size, these measures guarantee that individual information remains protected.

This database has several advantages. First, our data contain little measurement error and is not top coded. Thus, we can circumvent the problems associated with survey-based microdata. This allows us to have reliable estimates across the entire distribution of workers, including those at the top. Second, our dataset covers the population of formal firms and workers in Chile. Formality in Chile is among the highest in Latin America and the Caribbean, providing a very comprehensive sample. Formality in Chile among male workers aged 25 to 65 was 83% in 2003 (See Gasparini and Tornarolli, 2009).

We define labor income y_{it}, for worker i on year t, as total pre-tax labor compensation, including bonuses and variable payments.[2] Then, we deflate income by the average annual CPI to obtain comparable figures to those described in Guvenen et al. (2021). As it is common in this literature, to consider workers that have a meaningful attachment to the formal labor force and to avoid a few observations of very low earnings affecting our results, we trim observations below 1.5 months of the monthly minimum wage ($1.5Y_t^{min}$) in a year, following for example Mexico and Spain (Puggioni et al., 2022; Arellano et al., 2022), among others. This value in Chile was about USD 600 in 2022. We consider workers between 25 and 55 years old. Our final sample after cleaning contains about 120 million year-worker observations.

In our main analysis, we focus on log-labor earnings. We complement these results using "residual" labor earnings: the earnings levels after controlling for age and gender-fixed effects. To measure income volatility, we calculate the growth rate of y_{it} between two consecutive years.

[2]More specifically, total labor income includes the base salary, incentives and rewards, payments for agreements, sales commissions, and overtime payments; it does not include social security payments.

TABLE 2: Descriptive Statistics for Baseline Yearly Labor Earnings Sample. Period averages.

Period	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9
2004-2012	618	1,135	1,899	4,337	7,905	15,048	28,238	42,763	90,301	205,057
2004-2007	567	1,047	1,739	3,722	6,781	12,978	24,510	37,179	80,852	196,607
2008-2012	669	1,217	2,034	4,952	8,929	17,118	31,000	46,487	96,841	217,905
2013-2024	841	1,637	2,849	6,203	11,146	20,379	36,905	52,885	108,949	254,801
2013-2019	781	1,526	2,615	5,719	10,524	19,286	35,373	50,678	103,961	247,324
2020-2024	957	1,863	3,043	6,784	12,778	22,727	39,947	57,313	111,940	263,861

Notes: Table shows descriptive statistics of our baseline sample. Nominal values are deflated to 2018 prices using Chilean CPI and transformed to US dollars using 2018 average exchange rate. Each statistic was obtained with more than 30 individuals.

For completeness, we also include in our results the growth rate over 5 years (which captures more permanent changes in labor earnings) and the arc-percent change of income, defined as $(y_{it} - y_{it-1})/(0.5 \times (y_{it} + y_{it-1}))$ where at least one of the components is allowed to be 0. We use this measure to study how workers' movements in and out of the labor force affect labor earnings volatility.

2.3 Descriptive Statistics

Tables 1 and 2 show selected statistics of the earnings distribution from our baseline sample. A few features are worth highlighting. First, our sample is about 60% men and 40% women. Second, similar to other economies, the Chilean working population has become older over time, with the share of workers 46 and older increasing by 3.8 percentage points in the slow phase respect to the fast growth phase. Third, between 2005 and 2018, men's and women's earnings across all income levels have grown. Finally, despite increasing employment rates for women—which increased from about 41% to 53% from 2004 to 2019—the gender earnings gap is relatively high while it has declined over the period analyzed from about 27% to 21 % between the fast and the slow growing phases of the economy.

3 Evolution of Earnings Inequality of Formal Employment in Chile

3.1 Earnings Inequality

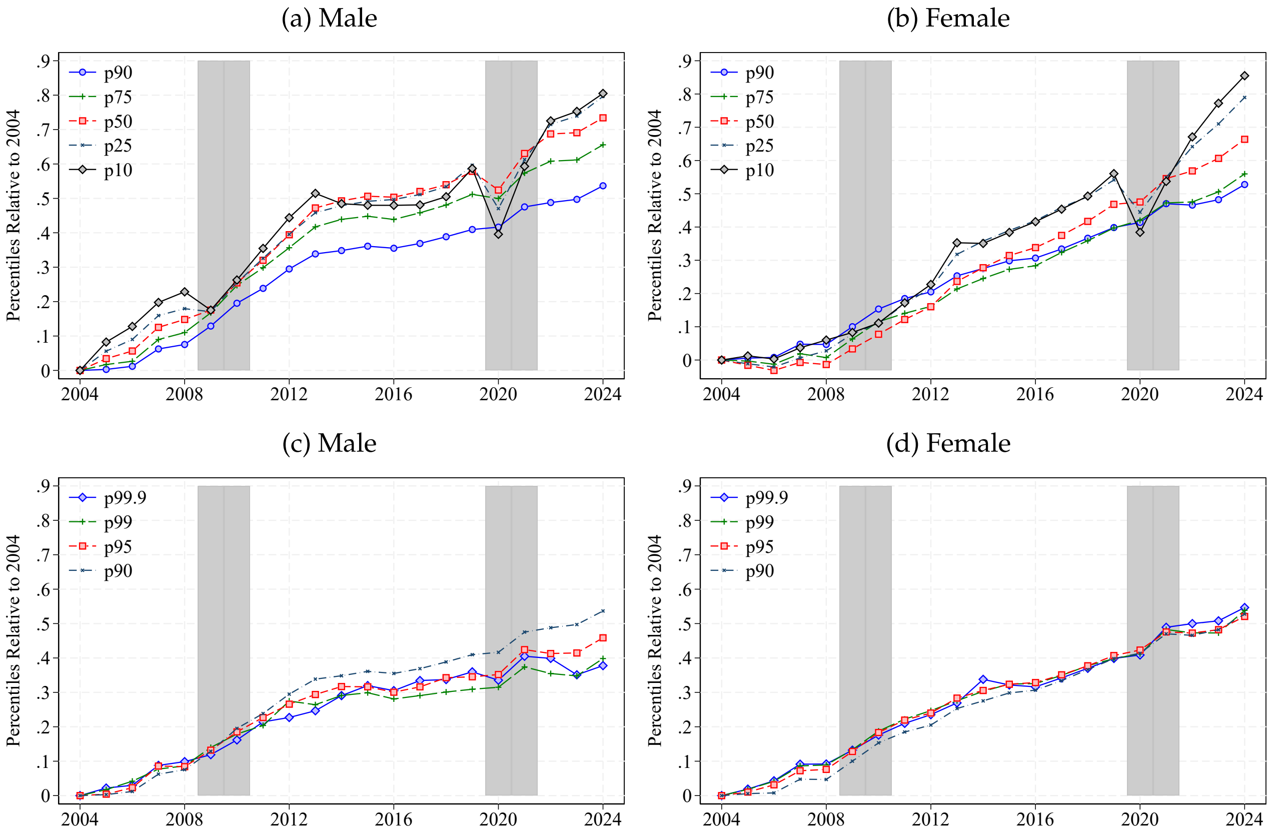
We begin our analysis by looking at the distribution of labor earnings distribution (above the threshold of $1.5Y_t^{min}$ in a year) between 2004 and 2024. Figure 2 shows the evolution of the percentiles of the income distribution in Chile, with Panels 2a and 2b showing P10, P25, P50, P75, and P90 for men and women, respectively. These two plots show that inequality has declined since 2005, with the P10 growth outpacing the growth of the P90 in every year but during the COVID-19 pandemic. Furthermore, we can clearly observe the effects of a slower growth rate after 2012 on men, with income growing much slower, starting in 2014 for all quintiles. In particular, the income growth rate of the P50 in the fast growth phase was 5.2%, and in the slow growth phase was 2.4% for men. Still, it was the lower ranks of the income distribution who experienced a faster growth during after 2012. Women's experience was different since they had a low-income growth rate until 2008, only increasing in speed after 2009. In the fast growth phase, average income growth was 3.7% for women. Conversely, women had steady income growth in most percentiles in Figure 2b.

Focusing on the slow growth phase, we observe a heterogeneous evolution across genders and along the income distribution. For instance, male workers at the P90 and P75 observed significantly slower income growth than workers at the median or less, except for P10. This fact means that inequality was falling not because workers at the bottom were gaining more but because workers at the top were experiencing a much lower income growth rate. Notice also the effects of the COVID-19 pandemic on income growth rates, which affected low-income men much more than high-income ones. Panel 2b shows that women's experience was similar. Despite much stronger growth, low percentiles experience less stable income growth, with recessions affecting them disproportionately. Below the P50, in both the Covid-19 and the Global Financial Crisis (GFC) recessions, the fall in income was stronger for workers at the bottom. However, the recovery benefited low income workers much more than high income ones, considtent with a countercyclicality of labor income inequality.

Figures 2c and 2d show the decomposition of the tenth decile into P90, P95, P99, and P99.9. The stagnation in income observed in Figures 2c and 2d in the P90 percentile is due to all divisiones of the tenth decile, with the 90th decile growing more strongly relative to the upper ranks of the income distribution. We conclude that the decline in income inequality observed in Chile from 2004 to 2019 is a general phenomenon, that also includes the top ranks of the income distribiution. Interestingly, these trends are also present in a developing-unequal country like Brazil (see Engbom et al., 2022) and in a developed-equal country like Denmark (see Leth-Petersen and Sæverud, 2022).

Figure 3 shows the dispersion in log-earnings, the P90-P10, as a measure of inequality. For both men and women, the dispersion in earnings levels is high; the P90-P10 dispersion has been around 260 log points over the 2004-2024 period. Chile experienced a decline in labor earnings dispersion

FIGURE 2: Evolution of percentiles of the income distribution with respect to 2004.

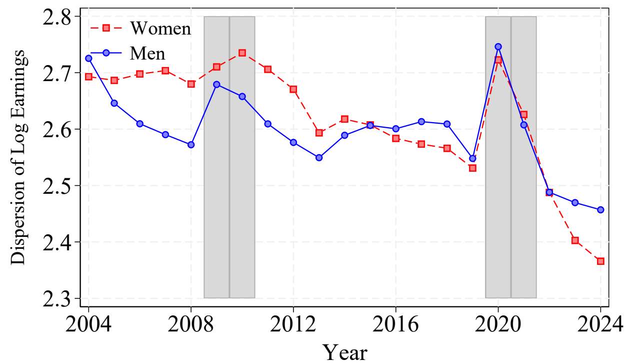


Notes: Figure 2 shows the evolution of the following percentiles of log earnings for men and women: Panels (a) and (b): P10, P25, P50, P75, P90; Panels (c) and (d): P90, P95, P99, P99.9. All percentiles are normalized to 0 in 2004. The gray bars representrecession years, defined as years with an output gap of -0.5 percent or less. See Section 2 for sample selection and definitions. Each statistic was obtained with more than 30 individuals.

during the period we analyzed, which was more pronounced in the slow growth phase and for women. Additionally, we observe a clear pro cyclical pattern in inequality: during recessions, inequality rises significantly (like in the COVID-19 pandemic, that it rose by about 20 log points), and recoveries have lower inequality, like 2022-2024, in which we observe a return to the negative trend in inequality experienced before the COVID-19 pandemic. Moreover, the dispersion in those years is the lower among the sample analyzed. In terms of the cyclicality, our findings are similar to the evidence found for Argentina, Brazil, and Mexico (see Blanco et al., 2022; Engbom et al., 2022; Puggioni et al., 2022).

To further analyze the source of income inequality trends and cyclicality, Figure 4 shows the P90-P50 and P50-P10 differences. In Chile, both tails account for a significant fraction of the overall P90-P10 dispersion, with a close-to-symmetric distribution between 2004 and 2008, for men, after

FIGURE 3: Evolution of Dispersion of the Income Distribution.



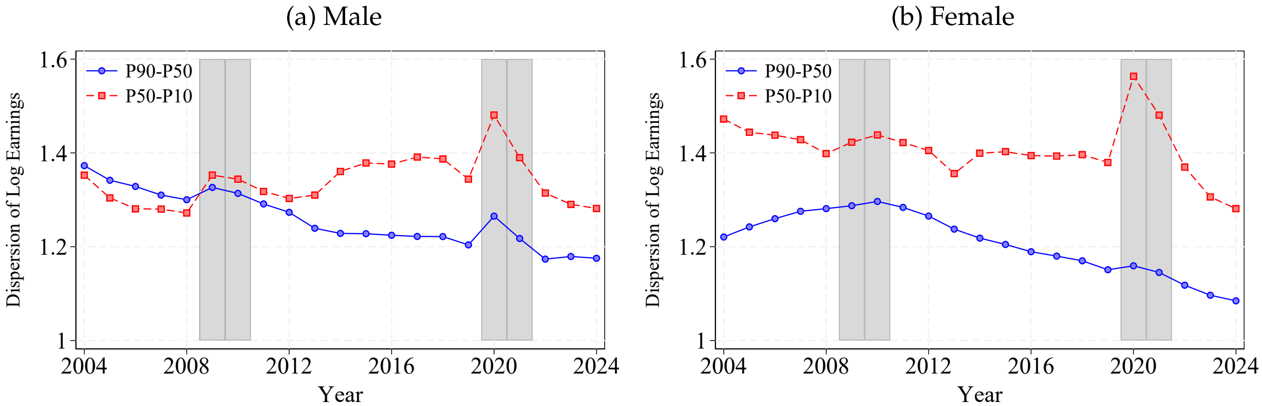
Notes: Figure 3 shows measures of dispersion of log labor earnings for men and women. The gray bars represent recession years, defined as years with an output gap of -0.5 percent or less. Each statistic was obtained with more than 30 individuals.

which there is a clear separation in the level of two tails. For wonen, the distribution has been tilted to the left, with a P50-P10 dispersion much larger than the P90-P50. Focusing on men, the right tail (P90-P50) is, on average, 125 log points, and the left tail is about 135 log points, but this difference only arises after 2010. This indicates that the overall decrease in income dispersion among men is due to a consistent increase in the income level of those at or below the median, whereas the income above the median has been more or less stagnant, hence reducing the gap between the P50 and P90. For women, the right tail is about 120 log points, and the left tail is about 140. This level of inequality is significant compared to developed and more equal countries like Norway and Sweden but similar to countries like Argentina and Brazil (see Guvenen et al., 2022). Similarly to men, what explains the decline in the dispersion is primarily the fall in the right tail of the distribution and ocurring mostly during the post 2012 period of low productivity growth.

3.2 Life-Cycle Earnings Inequality

Earnings inequality and the changes observed over time could, in principle, be separated into two components: inequality at young ages and the life-cycle evolution of earnings dispersion. To investigate each component, we document how within-cohort inequality evolves over the life-cycle and across different cohorts, that is, we compare how inequality evolves over time within the same cohort of individuals. Figure 5 plots the P90-P10 of log earnings in each age for four different cohorts of workers entering the labor market at age 25 from 1993 to 2010 so as we can follow them for at least 14 years. The colored markers connect different ages of the same cohort, thus showing

FIGURE 4: Evolution of Right and Left Tail Dispersion.



Notes: Figure 4 shows measures of dispersion in the right (P90-P50) and left (P50-P10) tails of the log labor earnings distribution for men and women. The gray bars represent recession years, defined as years with an output gap of -0.5 percent or less. Each statistic was obtained with more than 30 individuals.

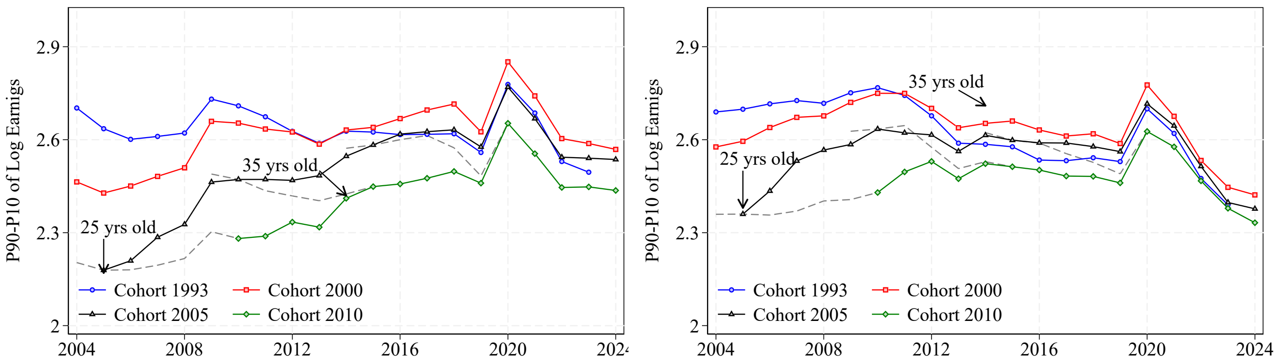
how within-cohort inequality evolves over the life cycle.

As mentioned above, log earnings dispersion is very high in Chile. This pattern is typical in every cohort with more than 200 log points in dispersion. We find significant heterogeneity in inequality levels across worker cohorts. In Chile, younger cohorts have lower inequality than older ones—as is typical over the life cycle. We find that inequality also depends on the starting point of the cohort. The 2005 cohort had lower inequality than the 2010 cohort. This may be due to the slower economic growth the 2010 cohort experienced, which depressed the growth of income at the top end of the distribution. The fact that the *level* inequality is fixed since the start of the working life of a cohort is also observed in other countries, such as the US (Guvenen et al., 2022), where most of the increase in income inequality oberved since the 1980s is due to cohort entering the labor market more unequal, which is the opposite what is happening in Chile.

Similarly to other countries, inequality increases with age but with some differences between cohort and gender. We find that for male workers, inequality increases with age, except for the oldest cohort, which had somewhat stable inequality over the period we analyzed. Inequality seems to converge when workers turn 40 years old. This is observed for the two oldest cohorts we have. Female workers, instead, have a somewhat different pattern. Inequality for the oldest female cohorts reaches a maximum in about 2010 and starts declining afterward. Instead, the youngest cohorts have an increasing pattern, stabilizing at some value. This value is about 260 log points for the 2005 cohort. For male and female workers, the youngest cohort has lower inequality and a less

FIGURE 5: Evolution of Labor Earnings Inequality by Cohort.

(a) Male (b) Female



Notes: Figure 5 shows the P90-P10 log earnings differential over the life cycle for selected cohorts of men and women. A cohort is defined by the year in which the cohort turns 25. Dashed lines connect individuals of the same age. The plots consider cohorts born between 1968 and 1985. Each statistic was obtained with more than 30 individuals.

steep age pattern than the other cohorts.

The life-cycle patterns of inequality in Chile are similar to the ones found in Mexico. They also find increasing inequality but with a maximum and that youngest cohorts suffer lower inequality than oldest cohorts (see Puggioni et al., 2022).

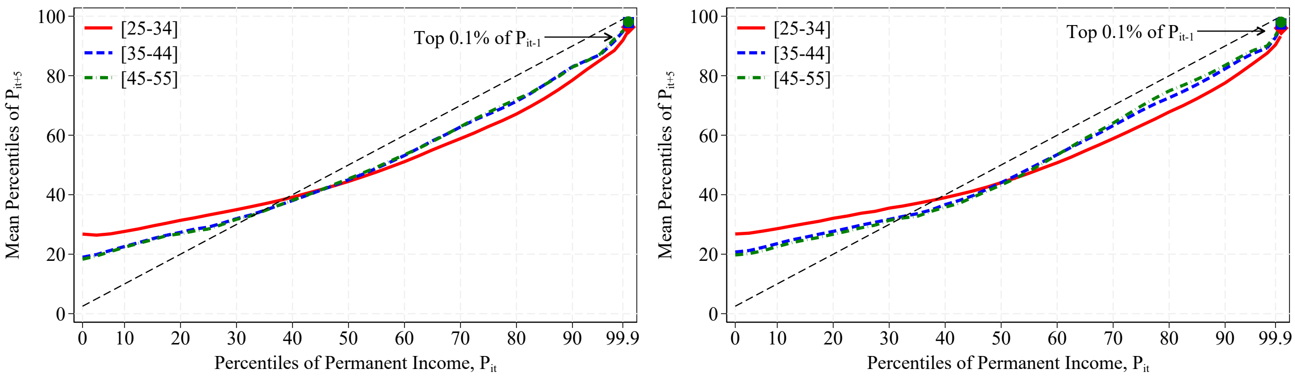
3.3 Income Mobility

Figure 6 shows a measure of income mobility in Chile. The x-axis has the percentiles of permanent income in period t, where permanent income $P_{i,t}$ is defined as s defined as the average earnings between $t-1$ and $t-4$, after controlling for age and time effets. The y-axis shows the mean percentile in $t+5$, and each of the percentiles in the x-axis is in that period. We show it separately by age and gender. In Chile, as in many countries (see Guvenen et al., 2022), the distribution is mean reverting, meaning that individuals at the bottom tend to move upwards and vice versa, implying that at the bottom of the distribution, individuals tend have a rank above rge 45-degree line and the opposite happens at the bottom. As a consequence, individuals below 35% of the permanent income distribution tend to move upward on average. On the other hand, individuals above 35% tend to move downward on the ranking, but the change is slower than for bottom percentiles. These patterns are more salient for younger workers and have a stronger mean reversion, as the flatter red-solid lines show.

Also, surprisingly, there is some upward mobility at the very top. The dots and squares at

FIGURE 6: Income Mobility.

(a) Male (b) Female



Notes: Figure 6 shows rank-rank mobility measures. For each age groups, we calculate the average rank of an individual in period t+5 conditional on the rank in period t within an age group. Each statistic was obtained with more than 30 individuals.

the top are below the 45-degree line, meaning that workers at the very top, to some extent, move downwards. Thus, there is some income mobility in top incomes in Chile. However, this mobility at the top is small relative to Scandinavian countries like Denmark (see Leth-Petersen and Sæverud, 2022).

4 Dynamics of the Distribution of Earnings Growth

In this section, we characterize income volatility by documenting the properties of the distribution of individual earnings changes in Chile. We measure earnings change as the log growth rate of residual earnings between years t to $t+k$, $g_{it}^k = \tilde{\varepsilon}_{it+k} - \tilde{\varepsilon}_{it}$ for $k = \{1, 5\}$.[3] We obtain residual earnings, $\tilde{\varepsilon}_{it}$, by regressing log earnings in each year on a set of age dummies for men and women separately.[4]

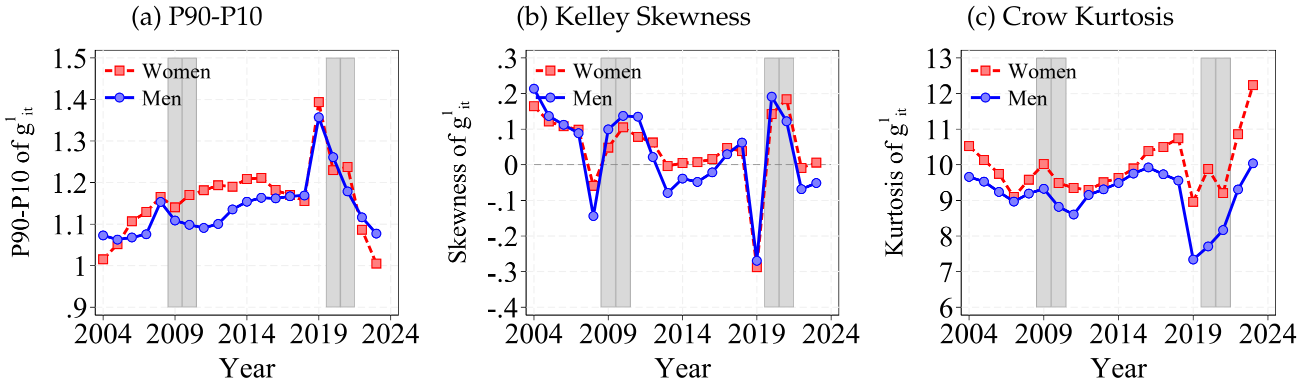
4.1 Higher-Order Moments of Individual Earnings Growth

Starting from Guvenen et al. (2014), a growing body of literature has documented that idiosyncratic earnings changes display strong non-Gaussian features—such as left skewness and excess kurto-

[3]We consider *expected* changes in income but we plot them backwards.

[4]Notice that the log growth measure only applies to individuals with earnings above the minimum threshold, Y_t^{min}, in periods t and $t+k$ excluding earnings changes of individuals that have little or zero earnings. To account for this, we construct log income growth between t and $t+k$ for those who have earnings above Y_t^{min} in t and above one-third of Y_t^{min} in $t+k$ so that we can better capture large declines in annual earnings. This slight change in the variable definition does not lead to any material difference in our results.

FIGURE 7: Moments of the $g^1 y_t$ Distribution time series.



Notes: Figure 7 shows the P90-P10, Kelley skewness and excess Crow-Siddiqui kurtosis of 1 year earnings growth for men and women. The gray bars represent recession years, defined as years with an output gap of -0.5 percent or less. Each statistic was obtained with more than 30 individuals.

sis—and these deviation from normality vary over workers of different characteristics and over time (e.g., Arellano et al., 2017; Guvenen et al., 2021).

In this section, we follow this literature and investigate how the earnings growth distribution evolves over time in Chile and over the two the business cycles we have in our data. In this section, we follow the GRID project and we document features of the distribution of annual earnings for one-year earnings growth and we relegate to Online Appendix the results for five-years earnimgs growth. Also, in the main text, we report percentile-based moments which have become standard in the study of income risk, (e.g., Kelley skewness and Crow-Siddiqui kurtosis), and have the advantage fo be robust to outliers. We include standardized moments in Online Appendix.

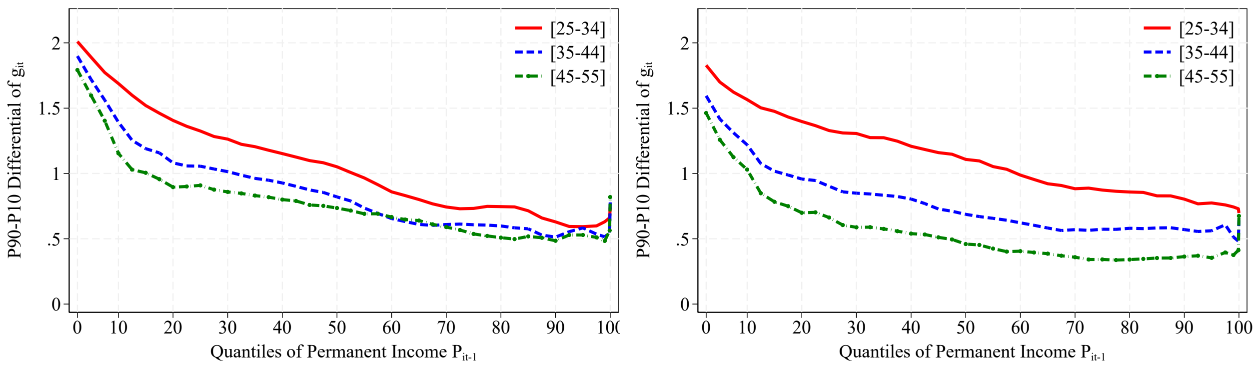
Volatility. In Chile, the overall volatility of earnings does not have significant differences by gender (Figure 7a). For men and women, the volatility of earnings measured by the P90-P10 is about 110 log points. These values are high relative to advanced countries like Norway (Halvorsen et al., 2022) and Spain (Arellano et al., 2022), in which men have this measure of dispersion at about 50 log points. These figures, nonetheless, are below the values found in developing economies like Brazil and Argentina (see Engbom et al., 2022; Blanco et al., 2022). We also find that in Chile, maybe due to the growth deceleration process is experiencing, the dispersion has a positive trend at least until 2019. In 2006, it was about 100 log points for women and 110 for men; in 2018, it was about 120 for both men and women. These trends are present only in developed countries like Norway and Denmark. This indicates that the decline in income dispersion discussed in the previous section has not been accompanied by a similar decline in income instability. We also observe a significant cyclicality of earnings growth dispersion. During the GFC for instance, men experience a rise in dispersion which is small relative to what happened during the COVID-19 pandemic, when the volatility increased significantly by more than 20 log points. After the pandemic, however, volatility has declined below its pre recession levels.

Skewness. Panel Figure 7b shows the asymmetry in the distribution of earnings growth as measured by the Kelley skewness (Kelley, 1947), $\mathcal{S}_{\mathcal{K}} = \frac{\text{(P90-P50)}-\text{(P50-P10)}}{\text{P90-P10}}$. In Chile, Kelley's skewness of log earnings growth averages about zero for men and women during our sample period. These measures are highly procyclical for both men and women, indicating that the probability of experiencing large income losses increases significantly in recessions. For instance, during the GFC, the Kelley skewness changed by about 0.2 percentage points, declining from about 0.1 to -0.1, but recovering quickly in 2009. To put things in perspective, this indicates that the distribution of earnings growth was tilted to the right before the recession, with the right tail accounting for 55% of the total dispersion of earnings growth. That value declined to 45% during the GFC. Moreover, men suffered more than women, with the skewness for women falling by about 8 percentage points less. In contrast, during the COVID-19 pandemic, both genders suffered similarly, with the skewness of earnings growth falling from about 0.05 to -0.3 for women and men. These large drops recovered and overshooted in 2021 to levels above pre-pandemic values and returned to normal in 2022.

An important fact from Figure 7b is the change in levels of skewness in 2013 in men and 2014 in women. The skewness was significantly positive in the fast growth phase, averaging about 0.1. However, in the slow growth phase, the skewness was about zero. This means that the perspectives for workers transitioned from having high probabilities of significant raises (with respect to large cuts) to having equal probabilities of significant raises and cuts. One of this paper's main results is that due to slow economic growth, Chile worsened the income growth perspectives, even for those workers that keep stable employment relatioships, as we will show in Section 5. This phenomenon mainly affected men because they had a larger skewness in the fast phase, and the transition was quicker than for women that saw their skewness fall slower.

Kurtosis. Figure 7c shows the excess kurtosis of one-year earnings changes for men and women as measured by Crow and Siddiqui (1967) kurtosis, $\mathcal{C}_{\mathcal{K}} = \frac{\text{(P97.5-P2.5)}}{\text{P75-P25}} - 2.91$, where 2.91 corresponds to $\frac{\text{(P97.5-P2.5)}}{\text{P75-P25}}$ of a normal distribution. Despite the significant changes observed in the distribution

FIGURE 8: Dispersion of Earnings Growth by Permanent Earnings and Age



(a) Men (b) Women

Notes: Figure 8 shows the P90-P10 of the log growth rate of residual earnings for men and women within quantiles of the PE distribution, P_{it-1}. The quantiles considered in this plot are every 2.5% until percentile 97.5, we include the 99 percentile and the top 0.1%. The plot shows an average of all years. Each statistic was obtained with more than 30 individuals.

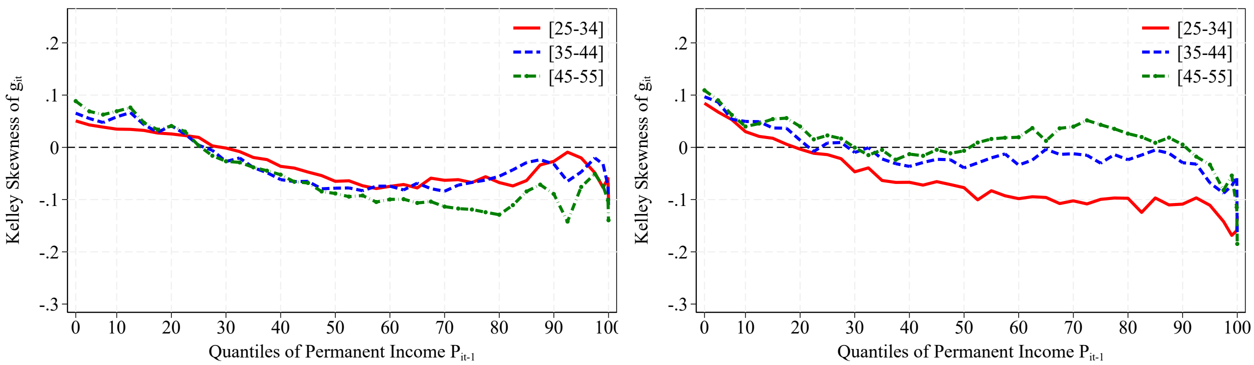
of earnings in Chile during the 21 years covered by our data, the kurtosis of earnings growth has remained relatively stable at about 9 for both men and women over our sample period. Women had always had a larger kurtosis than men and converged to men levels in 2015. The two growth phases in Chile are also present in this series, but the changes seem insignificant. The two recessions Chile experienced over this sample had different effects on the excess kurtosis. During the GFC, kurtosis increased slightly for men and strongly for women, and during COVID-19, kurtosis declined significantly for both men and women.

4.2 Heterogeneity in Idiosyncratic Earnings Changes

Having investigated how income risk varies over time in the aggregate, in this section we exploit the size of our dataset to study how the properties of earnings growth vary by age and within narrower population groups as defined by permanent earnings , P_{t-1}^i, or PE. We follow the approach of Guvenen et al. (2022) and in each year t (starting 2005), we split workers into three age groups: 25–34, 35–44, and 45–55, and within each gender-age group, we rank individuals into 40 quantiles with respect to their level of P_{t-1}^i. Finally, within each quantile, we compute moments of residual earnings growth, g_{it}^k, between periods t and $t+k$. Our figures plot the average of these moments over the 18 years starting in 2007, which is the first year in which we can define the permanent income, and 2022 for one-year income changes.[5]

[5] In Online Appendix we present the five-year income changes, where the main conclusions do not change. Additionally, in the Online Appendix we present the one and five-year analysis with the centered moments.

FIGURE 9: Kelley Skewness of Earnings Growth by Permanent Earnings and Age



(a) Men

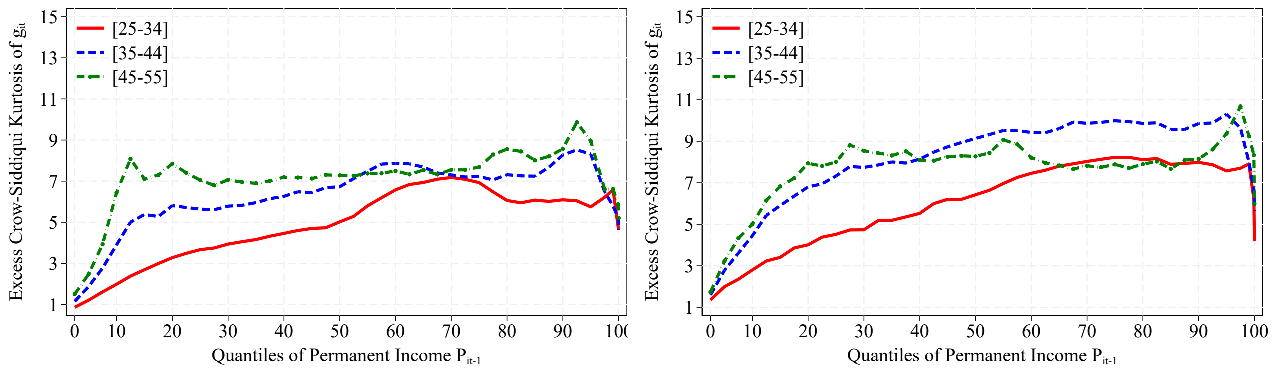
(b) Women

Notes: Figure 9 shows the Kelley skewness of the log growth rate of residual earnings for men and women within quantiles of the PE distribution, P_{it-1}. The quantiles considered in this plot are every 2.5% until percentile 97.5, we include the 99 percentile and the top 0.1%. The plot shows an average of all years. Each statistic was obtained with more than 30 individuals.

Heterogeneity in Volatility. For men and women, the dispersion of earnings shows a significant decline from low-income workers up to the 70th percentile of the distribution (Figure 8). Then, earnings growth dispersion is relatively flat between the 70th and 100th percentiles and only increases slightly at the top of the PE distribution. These patterns are similar for men and women, although for women dispersion is significantly higher across all ranks. For instance, for women 25-34, the decline along the PE distribution is slower, and the volatility is always larger than for the rest of the cohorts. Men 25-34 years old also have higher volatility. For men, this reverts at about the 60th percentile of the PE distribution. These figures are similar to those of other countries like Brazil and Spain.

Heterogeneity in Skewness. Skewness declines as we move from low to high PE workers (Figure 9) and this decline is more marked for men than for women, indicating that, at higher levels of income, the distribution of income growth tilts to the left, with negative changes becoming more likely than positive ones. For men, the Kelley skewness has a U-shaped pattern and is positive until the 30th percentile in all cohorts. Then, it turns negative for all age groups, and at about the 60th percentile, the data diverge. The oldest age group (45-55), skewness remains negative throughout the distribution, whereas for younger age groups, skewness tends to return to 0 above the 90th percentile. For Women, the patterns are somewhat different, with the youngest age group showing a significant negative skewness as we move from low to high income ranks. For the older age groups however, skewness is more or less flat, hovering around 0. This decreasing pattern also exists in developing economies like Mexico (Puggioni et al., 2022). A developed economy that

FIGURE 10: Kurtosis of Earnings Growth by Permanent Earnings and Age



(a) Men (b) Women

Notes: Figure 10 shows the coefficient of excess Crow-Siddiqui Kurtosis of the log growth rate of residual earnings for men and women within quantiles of the PE distribution, P_{it-1}. The quantiles considered in this plot are every 2.5% until percentile 97.5, we include the 99 percentile and the top 0.1%. The plot shows an average of all years. Each statistic was obtained with more than 30 individuals.

shows these patterns is Denmark (Leth-Petersen and Sæverud, 2022).

Heterogeneity in Kurtosis. Finally, we look at the heterogeneity of the kurtosis of labor earnings growth for men and women. Figure 10 shows the within-permanent income Crow-Siddiqui measure. Similar to other countries, the distribution of earnings growth exhibits excess kurtosis across different workers and age groups, indicating that for most workers, the year-to-year changes in income are small, although for some individuals, these changes might imply large gains or losses in labor earnings. Interestingly, the level of excess kurtosis is quite similar for men and women, and increases as we move from low to high permanent income levels. Taken together, these results suggest that the labor income process in Chile differs significantly from a Gaussian process, with low-income workers being characterized by a high income dispersion, high skewness, and low kurtosis. On the opposite side, for high-income individuals, dispersion is significantly lower, but they are relatively more exposed to higher downside risk and potentially extreme earnings growth realizations. One potential explanation is that low-income workers are more likely to lose their jobs than high-income workers. As we show in the next section, although this explanation has merits, non-Gaussian features are also present that maintain stable employment relationships.

5 Monthly Frequency Facts and the Role of Labor Market Transitions

The results presented in the previous section show a full picture of the earnings and earnings growth distribution for Chile. These results, however, were based on annual data, which typically masks a significant amount of variability that occurs are a higher frequency. In particular, annual earnings growth do not tells whether the observed features of the earnings distribution are due to employment trasitions or are also present for workers in more stable jobs, who are potentially more isolated from earnings fluctuations. To fill this gap, in this section, we study the evolution of the income change distribution at a business cycle frequency.

In our analysis, we take advantage of a monthly panel of employer-employee data we have available. This is another dataset, from the unemployment benefit manager, which has records on monthly labor earnings as well as other demographic characteristics. Here, we show the cyclical behavior of the moments of the income change distribution in the aggregate, and also we split the moments of the labor income change distribution by labor market flow, considering transitions between employment and unemployment, job to job transitions, and stayers. Using this information, we study the contribution of these flows to the cyclicality of the overall moments of the income change distribution.

5.1 Data

For our monthly results, we draw information from the administrative dataset of the unemployment benefit management institution (AFC, by its Spanish acronym) to obtain the time series for wages and labor transitions for the universe of formal-private workers in Chile (i.e., workers with a formal contract who pay pension contributions), excluding workers in the public sector. The raw labor data contains information about workers' monthly salaries, the use of unemployment benefits, and employer-employee matches from January 2002 to December 2021. This data also includes the educational level, gender, firm industry, and amount saved in the unemployment insurance account, among other variables. The total number of observations is about 900 million, with monthly observations hovering at around five million per month since 2014. To account for different transitions between jobs and in and out of the sample (Job-to-Unemployment, for example), we fill with zeros the months without observed wages as explained below, which allows us to reach about a billion observations in total if we consider the sample from Jan-2005 to Dec-2021.[6]

Sample Selection. Because of the high quality of our dataset (which contains information directly reported by firms, with little to no misreporting and no sample attrition), we do not conduct a

[6]See Appendix OA.3 for additional details of our database.

TABLE 3: DESCRIPTIVE STATISTICS FOR BASELINE LABOR EARNINGS SAMPLE

Sample Statistics, Employed							
	Total number of		Ratio of	Total number of			Total
Year	Workers	Firms	Men	$w_{it} > 0$	$w_{it} = 0$	$w_{it} < \underline{w}_t$	Observations
All ages workers	8,912,786	1,452,258	56.34%	715,757,539	392,068,363	576,198,553	1,107,825,902
[22,60] age workers	8,407,093	1,419,838	56.64%	671,622,988	340,080,526	463,434,849	1,011,703,514

Notes: This table show summary statistics of our database covering the period 2005m1 to 2021m12.

significant cleaning of our database to have the largest sample possible each period. At least for the twelve-month earnings changes, which is the main focus of our analysis, we are less concerned about the instabilities that people with short spells in the labor market may induce in our results and potential seasonal effects. The only cleaning we do relates to people with two jobs and on sick leave, where we consider the largest income in the former case and impute the last available income in the latter. Also, this database is top-coded, with about three percent of the database at the top. This is not a limitation for our exercise since we would likely underestimate income changes at the top of the distribution.[7]

As we explain below, in our sample, we follow workers who find a (formal) job at least once. We fill periods with a zero if they do not appear in our sample after entering. This is valuable information for building the tails of the income growth distribution with transitions between jobs and unemployment. We label the zero state as unemployment (recognizing that "unemployed" workers can be employed in the informal or public sectors) and impute a wage. The number of observations we have with positive income in the sample 2005-2021 is about 715 million, with an additional number of observations with zero income, which we impute, are 392 million. Thus, we reach a massive dataset of more than a billion monthly observations. In our final sample, we have about 9 million workers' IDs and 1.4 million firm IDs. The percentage of men in this sample is 56.34%, which is similar to our baseline results based on annual data.

Definition of Earnings. The main measure of labor earnings considers all sources of labor income, including base pay, tips, and bonuses. We do not include any measure of self-employment income. We denote these earnings by w_{it}. Then, we take logs, and for those observations below the minimum income ($\underline{w}_t$), we follow the procedure described in Guvenen et al. (2015), and transform income as follows:

[7] Our focus here is on formal workers. At the bottom of the earnings distribution, workers might use informal jobs to ameliorate the impact of negative income shocks. Our data—which is based on administrative records—cannot capture these sources of income.

TABLE 4: Time series means and correlations with output.

Moment	1-M	6-M	12-M	24-M
Avg_t^h	0.01	0.03	0.06	0.11
$Disp_t^h$	0.46	1.18	1.33	1.65
$Skew_t^h$	0.07	0.07	0.08	0.08
$Kurt_t^h$	134.5	14.03	10.72	7.01
$corr(Avg_t^h, \Delta^h Y_t)$	0.31	0.62	0.77	0.69
$corr(Disp_t^h, \Delta^h Y_t)$	-0.09	0.32	-0.21	-0.59
$corr(Skew_t^h, \Delta^h Y_t)$	0.43	0.76	0.85	0.81
$corr(Kurt_t^h, \Delta^h Y_t)$	-0.03	-0.09	-0.57	-0.28

Notes: This table shows time series average cross-sectional moments of the distribution of earnings growth for 1- to 24-months changes. Dispersion is measured by the P90-P10 percentiles differential, skewness by the Kelley Skewness, and kurtosis by the Crow-Siddiqui measure. The bottom panel shows the correlation of each moment and the corresponding change in GDP as approximated by the change in industrial production index (IMACEC). Each statistic was obtained with more than 30 individuals.

$$y_{it} = \begin{cases} \log\left(\underline{w}_t + \frac{\underline{w}_t}{10(\underline{w}_t+10)}\left\{(w_{it}) + 10U[0,1]\right\}\right) & \text{if } \ w_{it} \leq \underline{w}_t \\ \log w_{it} & \text{if } \ w_{it} > \underline{w}_t. \end{cases}$$

This way to account for monthly incomes below the real minimum income has a few advantages. First, it preserves the order of the income distribution and allows for capturing moments related to flows, including unemployed individuals whose responses across the business cycle are relevant, such as the UtJ and JtU flows. And second, fluctuations with zeros represent compositional effects, meaning for instance, that a negative skewness from separation must be due to higher-income workers losing jobs. Moreover, relative to the standard arc-percentage change, this measure is unbounded and does not generate large concentration of earnings observations in -2 or +2.[8]

Growth Rates and Moments of the Distribution. Define income growth between h periods as $\Delta^h y_{it} = y_{it} - y_{it-h}$. With this, we calculate the moments of the cross-sectional distribution of $\Delta^h y_{it}$. The moments we consider are the mean, variance (dispersion), skewness (asymmetry), and kurtosis (tailedness). To build high-order moments, we use their quantile-based measures similar to the ones described above.

[8]The arc-percent is defined as $d = \frac{x_t - x_{t-1}}{0.5\times(x_t + x_{t-1})}$ where one of the x can be equal to 0. This measure is bounded between -2 and 2.

5.2 The Distribution of Earnings Growth Over the Business Cycle

The top panel of Table 4 shows sample means of the first four moments of the distribution of earnings growth at four different horizons: 1, 6, 12, and 24 months. Over the period we analyze, Chile experienced consistent earnings growth, captured by a sample average of the average growth that increases as we move to longer horizons. Dispersion increases as well as we move from 1 to 24 months, as workers experience job mobility and changes in their income over time. Consistent with an overall increase in real earnings, the skewness of the distribution—measured by the Kelley measure—is positive along all the horizons and of more or less the same magnitude. As for the kurtosis, this tends to decrease as we move from shorter to longer horizons, indicating that a lower fraction of the distribution is concentrated around the median as we increase the horizon of income changes.

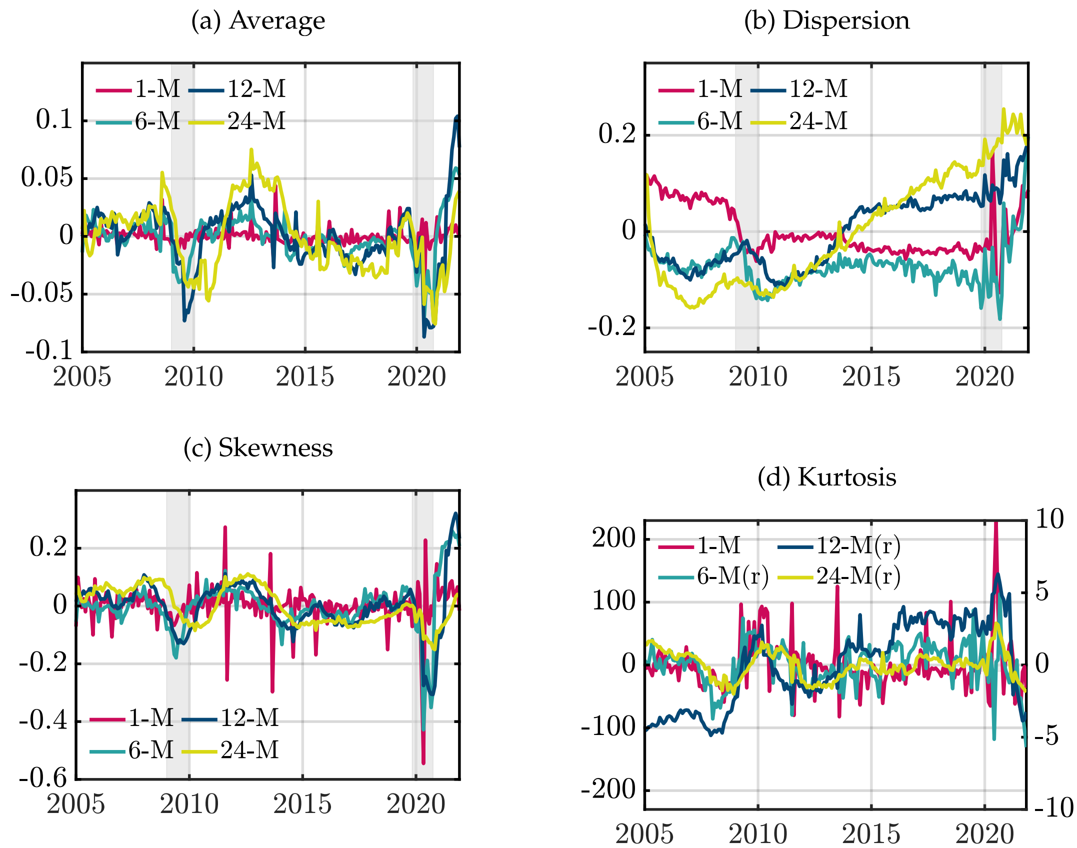
The bottom panel of Table 4 shows the correlation between each moment and GDP growth at the corresponding horizons.[9] As expected, the average income growth is positively correlated at all horizons, whereas the skewness is positively correlated, as it is typically found in the literature. Interestingly, the correlation between the skewness and GDP growth increases as we move to longer horizons, from 0.43 to 0.85 for 12-months changes in earnings. This implies that even at shorter horizons, the skewness of earnings growth is tightly linked to aggregate fluctuations. Instead, the dispersion of earnings growth does not show a clear pattern of correlations with the business cycle. Figure 11 depicts this more clearly, which shows the time series of the first four moments of the distribution of earnings growth with the shaded areas indicating recessions. Visually, Figure 11 shows the same as above: the average and the skewness fall in recessions for all horizons, whereas the dispersion does not seem to have a systematic behavior over time. Kurtosis, instead, tends to increase in recessions. These patterns—based on monthly data—are consistent with previous findings using annual earnings.

5.3 Labor Market Flows

Several papers have documented the cyclicality labor market transitions (see, e.g., Hubert and Savignac, 2024 and Gulyas et al., 2024 for monetary policy). Furthermore, empirical evidence shows that the distribution of earnings growth for workers who change employers is more dispersed and more left-skewed relative to workers who maintain stable employment relations (Guvenen et al.,

[9] We use the index IMACEC, which is the monthly GDP measure built by the Central Bank of Chile.

FIGURE 11: Moments of the Distribution of Monthly Earnings



Notes: This figure shows the time series of the moments of the cross-sectional distribution of income growth at different horizons. We show the average, dispersion, skewness, and kurtosis. Each plot shows a moment. Each figure shows the moment of 1-, 6-, 12-, and 24-month changes distribution. The figure considers data from 2005m1 to 2021m12. The data is detrended and deseasonalized (when it applies) with ARIMAX-13. Shaded areas represent recessions defined as periods with more than 6 consecutive months of y-o-y drop in GDP. Each statistic was obtained with more than 30 individuals.

2021). In this section, we link these two strands of literature and study the role of labor market transitions in the cyclicality of moments of the income change distribution.

To do so, we build different labor market transitions over the period we analyze income growth. That is, for a given growth rate $y_{it+h} - y_{it}$, we track the transitions (or not) between t and $t+h$, as follows: i) Stayers: individuals who work in the same firm in t and $t+h$. ii) Job-to-Job (JtJ): individuals who work in different firms in t and $t+h$. iii) Job-to-Unemployment (JtU): individuals who work in t and are unemployed in $t+h$. iv) Unemployment-to-Job (UtJ): individuals unemployed in t and with a job in $t+h$. In what follows, we consider 12-month changes ($h = 12$).

Table 5 describes the distribution of earnings growth after each of the transitions discussed before. Most of the observations in our sample correspond to stayers. We have that 39 percent of

TABLE 5: Moments of the Distribution of Earnings Growth for Different Transitions (2015).

Moment	**Stayers**	**JtU**	**JtJ**	**UtJ**	**Total**
Average	0.07	-0.79	0.11	0.85	0.07
Dispersion	0.51	2.07	1.70	2.00	0.6
Skewness	0.19	0.02	0.04	0.00	0.10
Kurtosis	5.38	1.96	2.62	1.98	7.59

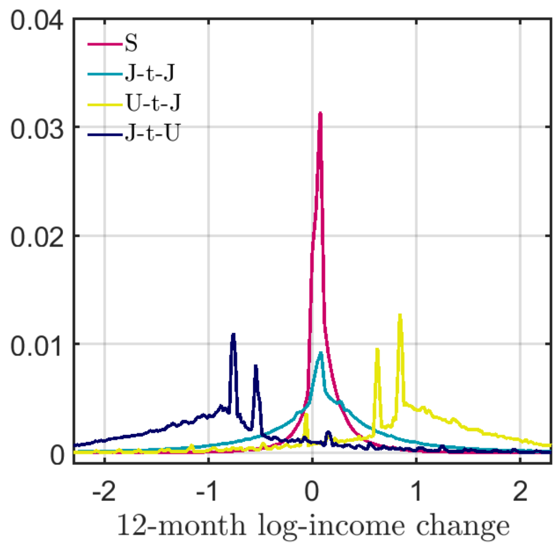
Notes: This table shows moments of the distribution of earnings growth among workers who experience different transitions in the labor market over 12 months. We show the moments of 2015. Each statistic was obtained with more than 30 individuals.

the sample is growth rates of workers who remained in the same firm. Many observations in our sample are people who were unemployed in both periods, which is about 24 percent of the sample. Then, JtJ transitions comprise a large proportion of our sample, 16 percent. Finally, JtU and UtJ correspond to about 10 percent each. In our sample, the remainder of transitions correspond to a tiny proportion.

Table 5 and Figure 12 characterize the distribution of earnings growth for each transition. Income growth is mainly due to JtJ transitions, with an average yearly growth of 11 percent. During this period, there was a significant increase in labor earnings in Chile, generating an average of 7 percent annual earnings growth for stayers. These two distributions are right-skewed. Naturally, transitions from unemployment and into unemployment imply positive and negative growth, respectively, but they by themselves are also skewed. JtU is negatively skewed, while the skewness of workers who experience a UtJ transition is mildly negative. This suggests significant income losses from unemployment. Figure 12 shows how these flows are distributed along income changes, with Stayers and JtJ centered in a mean close to zero, UtJ at the right of the distribution, thus contributing to the overall skewness, and JtU at the left, then contributing to the left skewness.

While the previous description is informative, we are more interested in the evolution of these measures over the business cycle. Figure 13 shows the average, dispersion, skewness, and kurtosis evolution over time, separated by the four labor market flows. The first to note is that average growth is highly procyclical, with a pronounced fall in Chile's two recessions over that period. Notably, the dispersion of all four flows does not seem to correlate with the business cycle. On the side of higher order moments, similar to the evidence on aggregate values for the skewness and kurtosis, they are highly correlated with the business cycle, skewness for stayers, JtJ, and JtU decreases in recessions, with a very pronounced fall for stayers. We find a similar pattern for the kurtosis. This moment for stayers is the most fluctuating, increasing significantly in recessions.

FIGURE 12: Distribution of twelve-month income changes conditional on labor market flow.



Notes: The figure shows the histogram of twelve-month changes for different labor market flows: stayers, Job-to-Job, Job-to-Unemployment, and Unemployment-to-Job transitions. The figure considers data from 2015m1 to 2015m12. Each statistic was obtained with more than 30 individuals.

This means that the distribution of stayers becomes more concentrated at the mean in recessions, indicating that wage changes become less likely overall.

Taken together, our results indicate that recessionary periods are characterized by significant changes in monthly earnings even at a high frequency, and it is the stayers who experience the largest increase in downside risk. This suggests that models in which the skewness of earnings growth is generated by means of an increase in unemployment risk are less likely to fully capture the extent of heightened risk that workers experience during a recession.

6 Conclusion

This paper describes the evolution of the distribution of income (inequality) and the distribution of earnings growth (income risk) in Chile, following the methods and analysis described in Guvenen et al. (2022). We use high-quality administrative records shared by the Internal Revenue Service that comprise the universe of formal workers (both public and private).

Chile shares several features of inequality and income risk with developing economies like Brazil and Mexico; Chile has high inequality in both men and women, has experienced a decline in inequality over the past two decades, and younger cohorts seem to have lower inequality overall.

Chilean workers also have highly volatile income growth but positive skewness and high-income growth over this period.

We relate these results to the fast growth and then deceleration phase Chile experienced over the two decades. We find that strong GDP growth contributes to reducing income inequality by the bottom of the distribution; this is, low-income workers benefited the most from growth in the fast growth phase. We find a substantial decline in inequality in the slow phase, but primarily due to high incomes suffering income stagnation. Second, we find that income risk is greatly affected by growth. Over the decades we have analyzed, we find that the dispersion of income growth distribution increased significantly, and the skewness declined, especially since 2014 when the slow growth phase kicked in more strongly.

Finally, using high-frequency monthly data we show that labor market flows also contribute to labor income risk; importantly, we find that income risk for people who stay in their jobs is more procyclical than other labor market flows like transitions from and to unemployment. We also show that job-to-job transitions also contribute to the overall income risk. We expect the increasing availability and analysis of the distribution of earnings growth at frequencies lower than a year might better inform monetary and fiscal policy, which typically focuses on short to medium-term fluctuations.

The indicators provided in this paper are complements to usual figures provided by statistical agencies like unemployment and labor market participation. They shed light on the health of the labor market and its possible implications for macroeconomic fluctuations and consumption more in depth so they are useful for policy analysis.

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Appendix for "Characterizing Income Risk in Chile and the Role of Labor Market Flows"

by Mario Giarda, Ignacio Rojas, and Sergio Salgado

OA.1 Descriptive statistics year-by-year

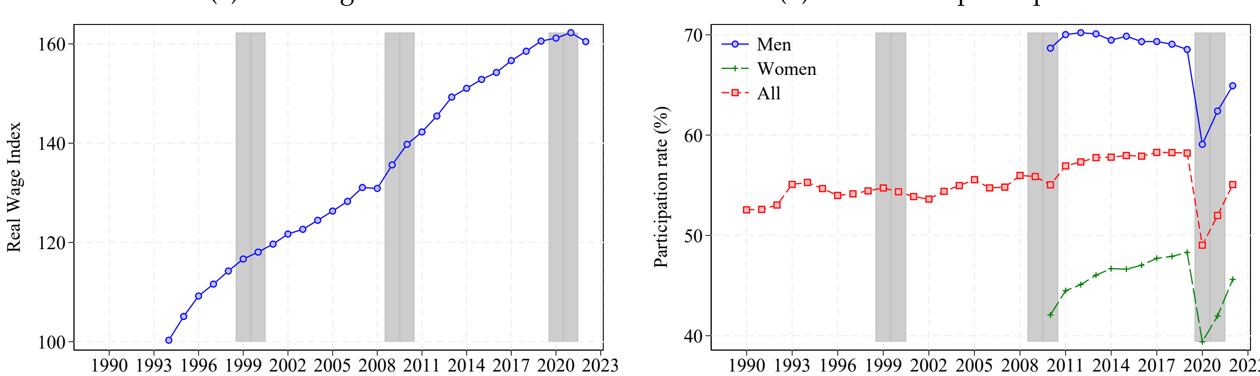
TABLE OA.1: Evolution of percentiles

Year	N	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9
2004	2,708,578	544	986	1,619	3,580	6,565	12,692	24,320	36,887	77,567	188,322
2005	2,966,101	561	1,035	1,719	3,674	6,685	12,820	24,410	36,992	78,609	191,939
2006	3,179,302	573	1,060	1,760	3,722	6,752	12,851	24,567	37,394	81,617	192,899
2007	3,399,451	590	1,108	1,856	3,913	7,122	13,549	25,742	39,441	83,613	201,267
2008	3,577,034	592	1,133	1,905	3,955	7,200	13,657	25,996	39,553	83,224	202,431
2009	3,620,907	615	1,123	1,857	4,055	7,441	14,444	27,318	41,414	88,861	206,989
2010	3,783,879	634	1,179	1,976	4,270	7,943	15,466	29,119	43,860	92,601	214,888
2011	3,969,942	655	1,256	2,130	4,540	8,413	16,134	30,270	45,611	93,732	225,340
2012	4,156,054	681	1,340	2,268	4,827	8,929	16,869	31,419	47,076	100,387	228,434
2013	4,271,033	779	1,496	2,493	5,219	9,617	17,863	32,857	48,601	99,964	234,223
2014	4,385,911	744	1,450	2,458	5,323	9,867	18,269	33,536	49,532	101,723	245,518
2015	4,472,082	758	1,466	2,496	5,455	10,080	18,511	34,108	49,798	102,188	248,629
2016	4,546,831	788	1,506	2,540	5,548	10,149	18,448	33,996	49,482	100,892	244,967
2017	4,622,916	810	1,527	2,582	5,697	10,373	18,943	34,648	50,237	102,135	249,310
2018	4,774,462	825	1,568	2,658	5,848	10,654	19,490	35,420	51,428	104,613	251,513
2019	4,868,117	871	1,685	2,869	6,218	11,122	20,159	36,346	52,135	104,734	255,611
2020	4,673,109	866	1,513	2,384	5,599	10,837	20,181	36,612	52,829	105,592	252,540
2021	4,725,951	902	1,725	2,833	6,293	11,844	21,605	38,841	56,294	113,001	270,177
2022	4,777,039	944	1,908	3,221	6,953	12,375	22,034	39,073	56,008	110,183	269,192
2023	4,633,032	1,005	2,014	3,421	7,287	12,605	22,366	39,312	56,247	109,893	259,557
2024	4,483,614	1,070	2,155	3,658	7,788	13,230	23,447	40,920	58,588	116,478	265,840

Notes: This Table shows summary statistics for the baseline sample. All nominal values are deflated to 2018 prices using the CPI of Chile and converted to US dollars using the average exchange rate in 2018. Each statistic was obtained with more than 30 individuals.

FIGURE OA.1: Labor market variables.

(a) Real wage index (b) Labor force participation



Notes: Figure OA.1 panel (a) shows the evolution of the real wage, normalized to the year 1993. Panel (b) shows the percentage of the population participating in the labor market; the gender desaggregation is available since 2010.The gray bars representrecession years, defined as years with an output gap of -0.5 percent or less. Source: National Employment Survey, National Statistics Institute (INE).

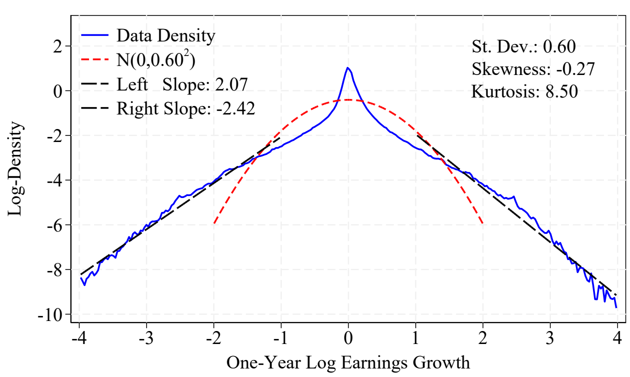
TABLE OA.2: Selected descriptive statistics

	N. Obs.		Mean income		Age distribution (%)		
Year	Female	Male	Female	Male	25-34	35-44	45-55
2004	910,411	1,798,167	9,990	12,040	40%	36%	23%
2005	1,013,349	1,952,752	10,012	12,257	40%	36%	24%
2006	1,111,807	2,067,495	9,997	12,517	40%	35%	25%
2007	1,219,689	2,179,762	10,385	13,234	39%	35%	26%
2008	1,313,083	2,263,951	10,369	13,402	39%	35%	27%
2009	1,353,053	2,267,854	10,910	14,001	38%	34%	28%
2010	1,435,076	2,348,803	11,463	14,943	38%	34%	28%
2011	1,521,639	2,448,303	11,872	15,695	38%	33%	28%
2012	1,615,979	2,540,075	12,189	16,568	38%	33%	29%
2013	1,688,111	2,582,922	12,879	17,346	39%	33%	29%
2014	1,764,140	2,621,771	13,279	17,746	38%	33%	29%
2015	1,821,525	2,650,557	13,621	17,876	38%	33%	29%
2016	1,871,422	2,675,409	13,799	17,728	38%	33%	29%
2017	1,918,697	2,704,219	14,242	18,018	38%	32%	29%
2018	1,993,056	2,781,406	14,718	18,401	38%	32%	29%
2019	2,040,324	2,827,793	15,264	18,865	38%	33%	29%
2020	1,949,206	2,723,903	15,334	18,442	37%	34%	29%
2021	1,972,677	2,753,274	16,328	20,073	36%	34%	29%
2022	2,023,828	2,753,211	16,567	20,551	34%	36%	30%
2023	1,962,513	2,670,519	17,034	20,555	32%	37%	31%
2024	1,904,495	2,579,119	17,992	21,483	29%	39%	32%

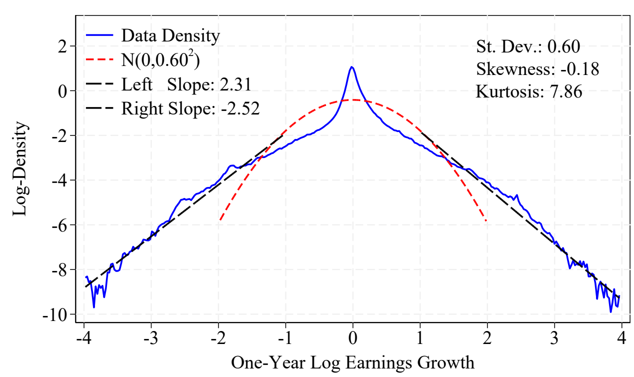
Notes: This Table shows summary statistics for the baseline sample, number of observations, mean income by gender and the age distribution of our sample. All nominal values are deflated to 2018 prices using the CPI of Chile and converted to US dollars using the average exchange rate in 2018. Each statistic was obtained with more than 30 individuals.

OA.2 Distribution and log-distributions of earnigs growth fast and slow-growing phases

FIGURE OA.2: Log densities 2015



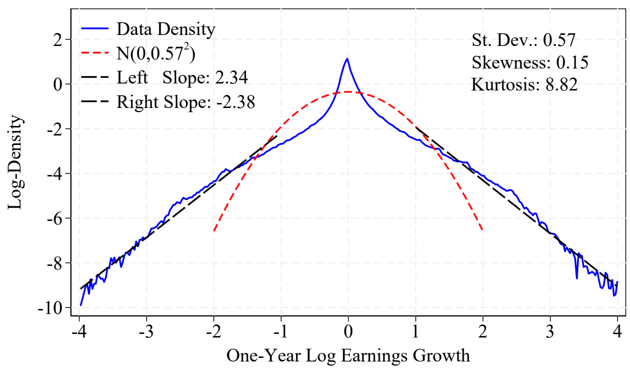
(a) Men



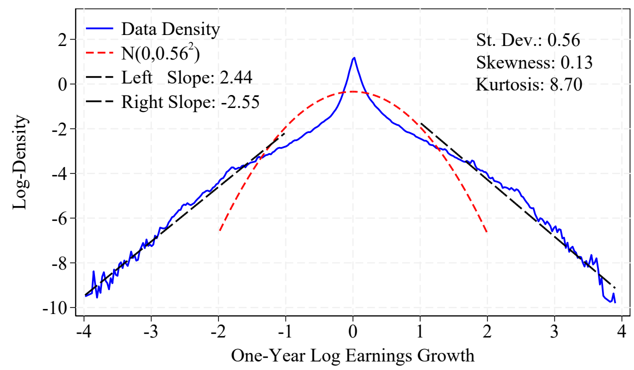
(b) Women

Notes: Figure OA.3 shows Empirical density of 1-year log earnings change and corresponding cross-sectional moments of the distribution of 1-year log earnings growth for men and women in 2015. See Section 2 for sample selection and definitions. Each statistic was obtained with more than 30 individuals.

FIGURE OA.3: Log densities 2005



(a) Men



(b) Women

Notes: Figure 9 shows Empirical density of 1-year log earnings change and corresponding cross-sectional moments of the distribution of 1-year log earnings growth for men and women in 2015. See Section 2 for sample selection and definitions. Each statistic was obtained with more than 30 individuals.

OA.3 Unemployment Insurance Mechanism

Every new employment contract signed after October 2002 is automatically enrolled in the Unemployment Insurance (UI) scheme, provided the individual is over 18 years old. For contracts signed prior to October 2002, affiliation with UI is voluntary. However, there are exceptions to who can participate in UI. Employees in the public sector, military sector, and self-employed individuals are not eligible for UI coverage. The payments from the insurance are determined based on a percentage of the employee's last ten monthly income. The percentages decrease over time: 70% for the first month, 60% for the second month, 45% for the third month, 40% for the fourth month, 35% for the fifth month, and 30% from the sixth month onwards. Financing UI is divided based on the nature of the employment contract. For long-term contracts, the employee contributes 0.6% of their monthly wage, while the employer contributes 2.4% (with 1.6% going to the employee's account and 0.8% to the solidarity fund). For short-term contracts, the employee does not contribute, but the employer contributes 3% (with 2.8% going to the employee's account and 0.2% to the solidarity fund). Any remaining funds from the UI contributions are directed towards the pension fund, and these funds are inheritable. Figure OA.4 shows the evolution of yearly observations.

FIGURE OA.4: Number of Yearly Observations

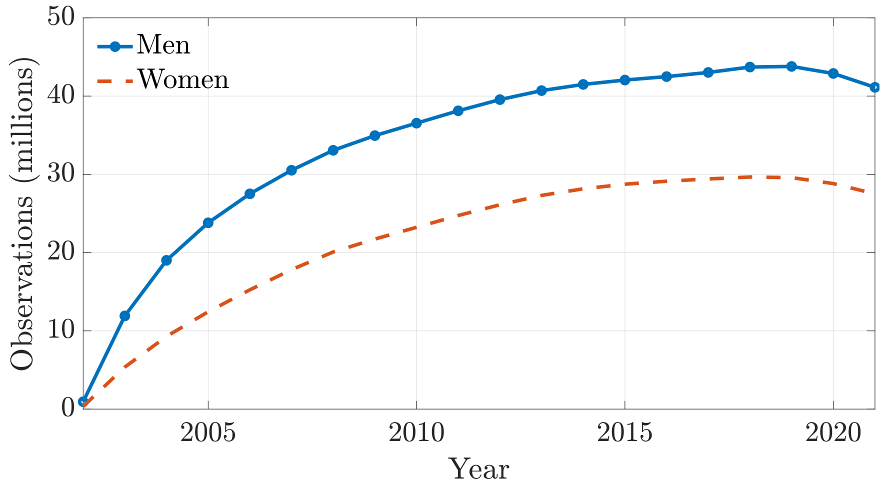
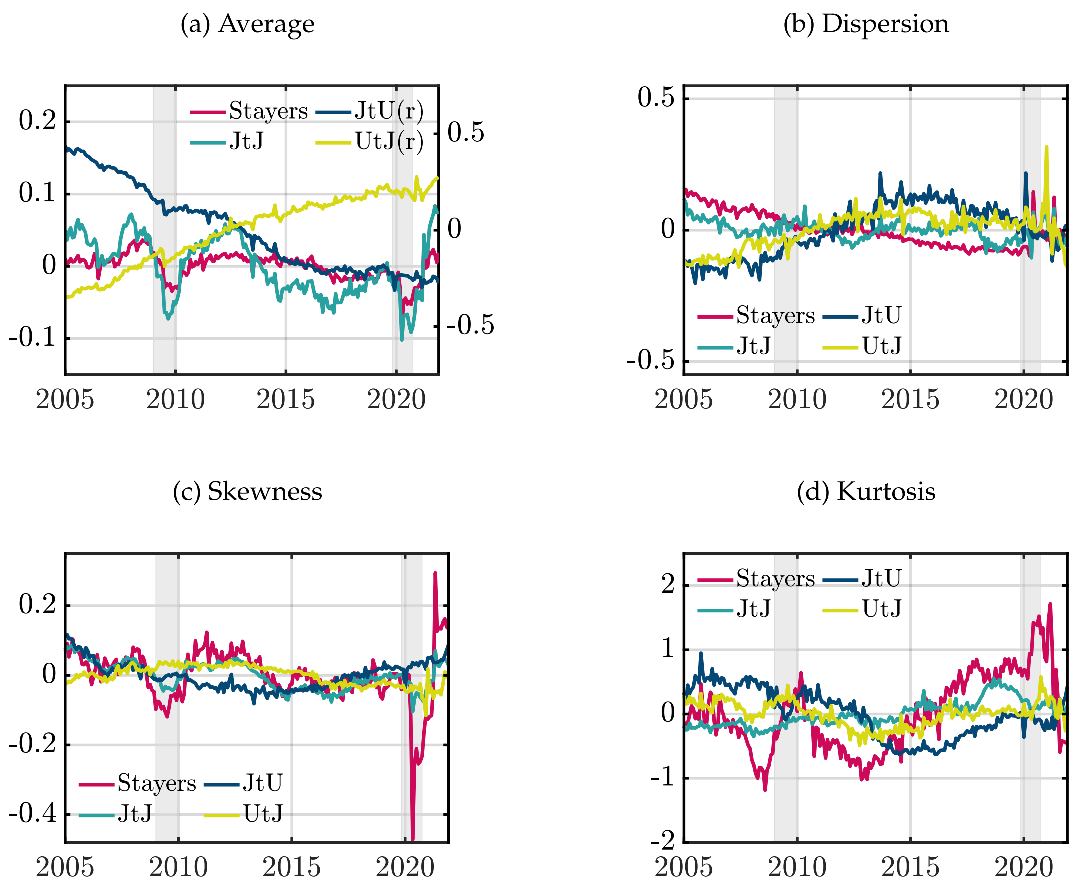


FIGURE 13: Time-series of moments of the twelve-month income changes conditional on labor market flows.



Note: This figure shows the time-series of the moments of the cross-sectional distribution of income growth at 12 month for different labor market flows. We show the average, dispersion, skewness, and kurtosis. Each plot shows a moment. Each figure shows the moment of different labor market flows: stayers, Job-to-Job, Job-to-Unemployment, and Unemployment-to-Job transitions. The figure considers data from 2005m9 to 2021m12. The data are detrended. Shaded areas represent recessions defined as periods with more than 6 consecutive months of y-o-y drop in GDP. Each statistic was obtained with more than 30 individuals.

ONLINE APPENDIX:

Characterizing Income Risk in Chile and the Role of Labor Market Flows*

Mario Giarda† Ignacio Rojas‡ Sergio Salgado§

December 2, 2025

This online appendix complements the paper by publishing the remainder plots generated by GRID and are not included in the main paper.

*The views expressed are those of the author and do not necessarily reflect the views of the Central Bank of Chile or its board members. This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities by virtue of collaboration agreements signed with these institutions.To secure the privacy of workers and firms, the CBC mandates that the development, extraction, and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. All the analysis was implemented by the authors and did not involve or compromise the IRS. The information contained in the databases of the Chilean IRS is of a tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.

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†Central Bank of Chile; mgiarda@bcentral.cl

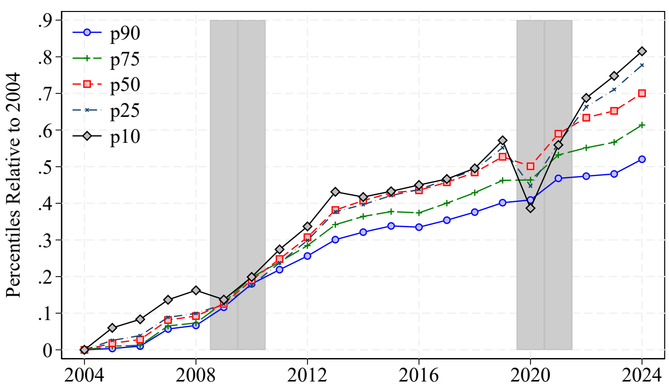
‡University of Minnesota; irojas@bcentral.cl

§The Wharton School, University of Pennsylvania; ssalgado@wharton.upenn.edu

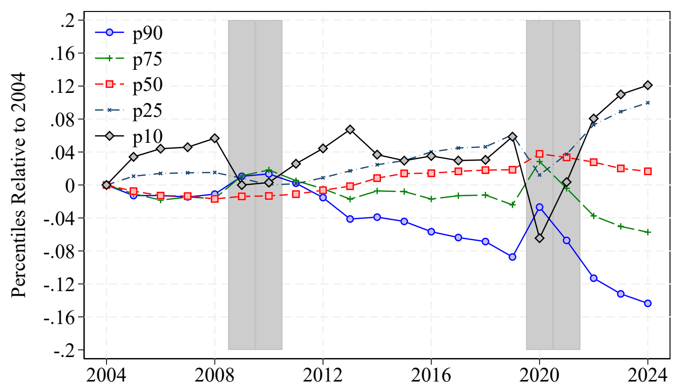
OA.1 Trends in Inequality: Additional Plots

FIGURE OA.1: Evolution of percentiles of the income distribution with respect to 2004. All workers, women, and men.

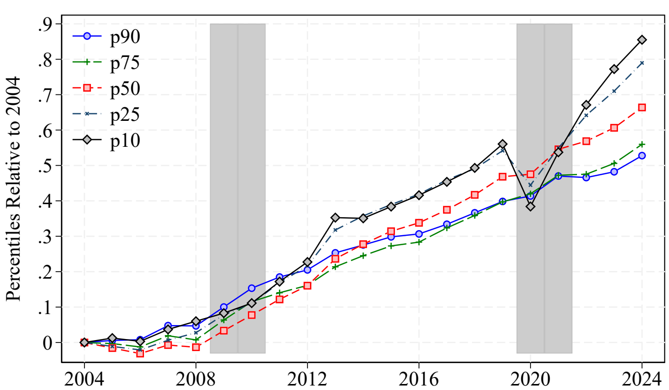
(a) All: log-earnings



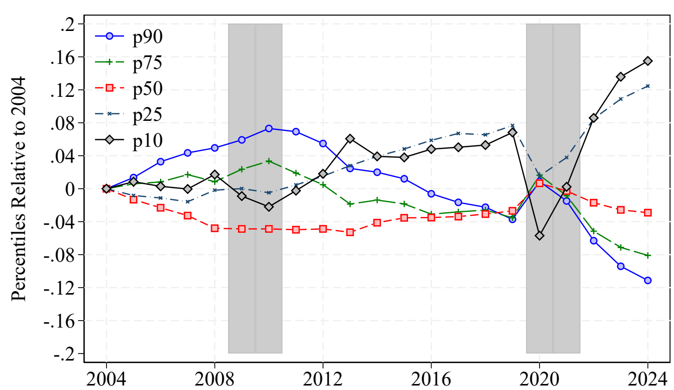
(b) All: residual earnings



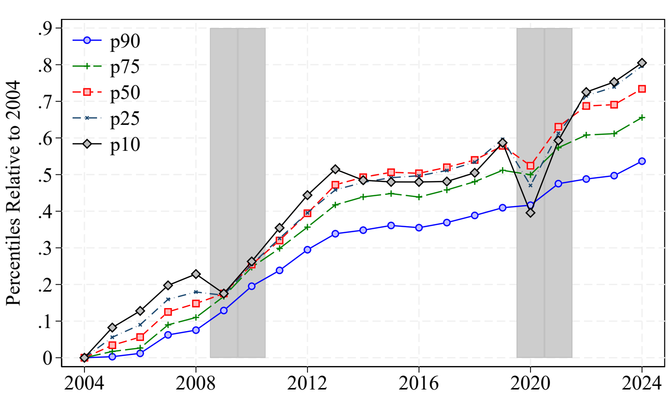
(c) Women: log-earnings



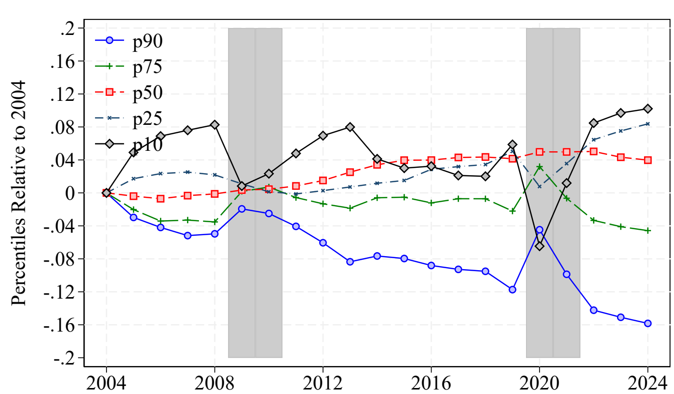
(d) Women: residual earnings



(e) Men: log-earnings

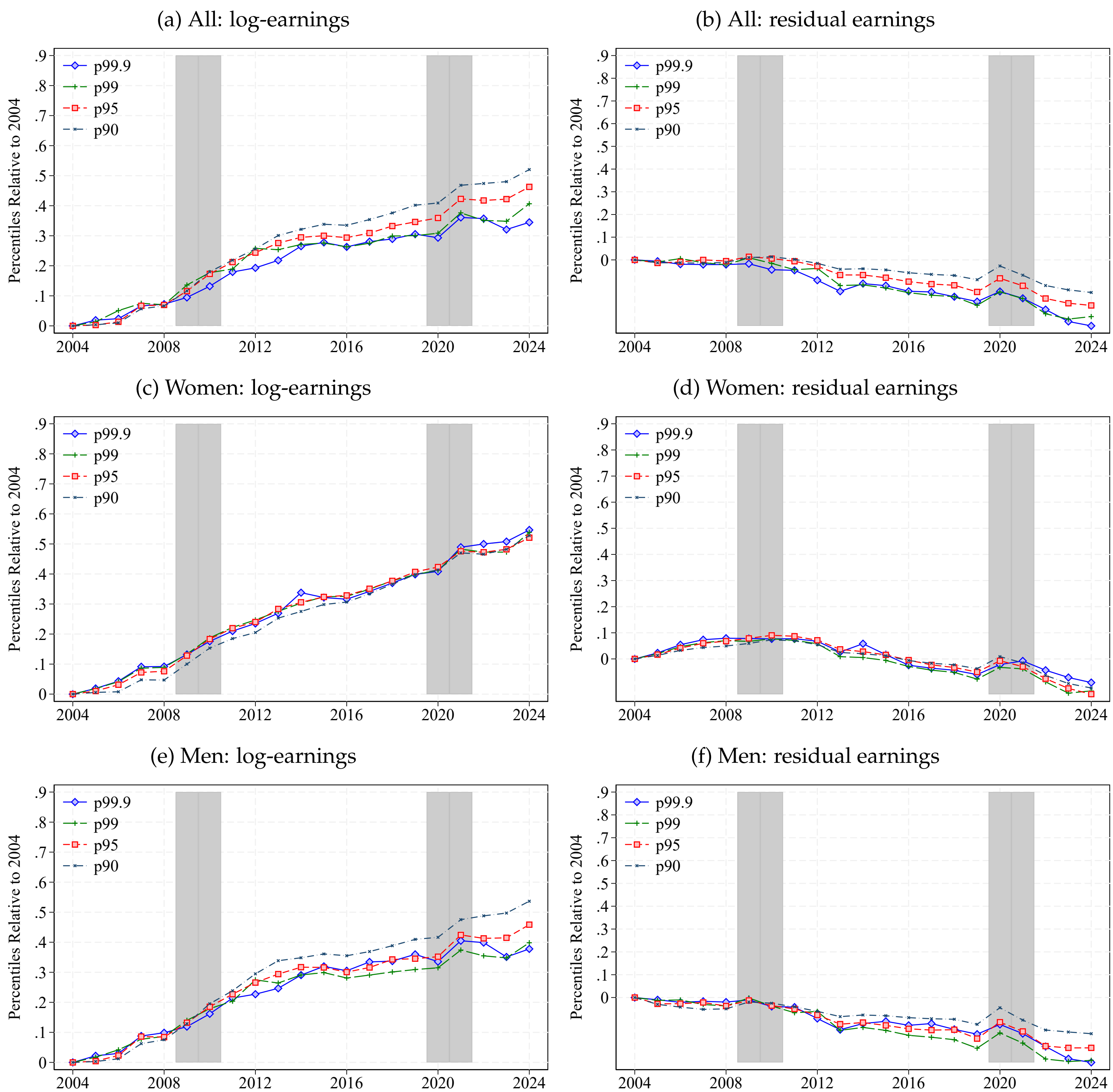


(f) Men: residual earnings



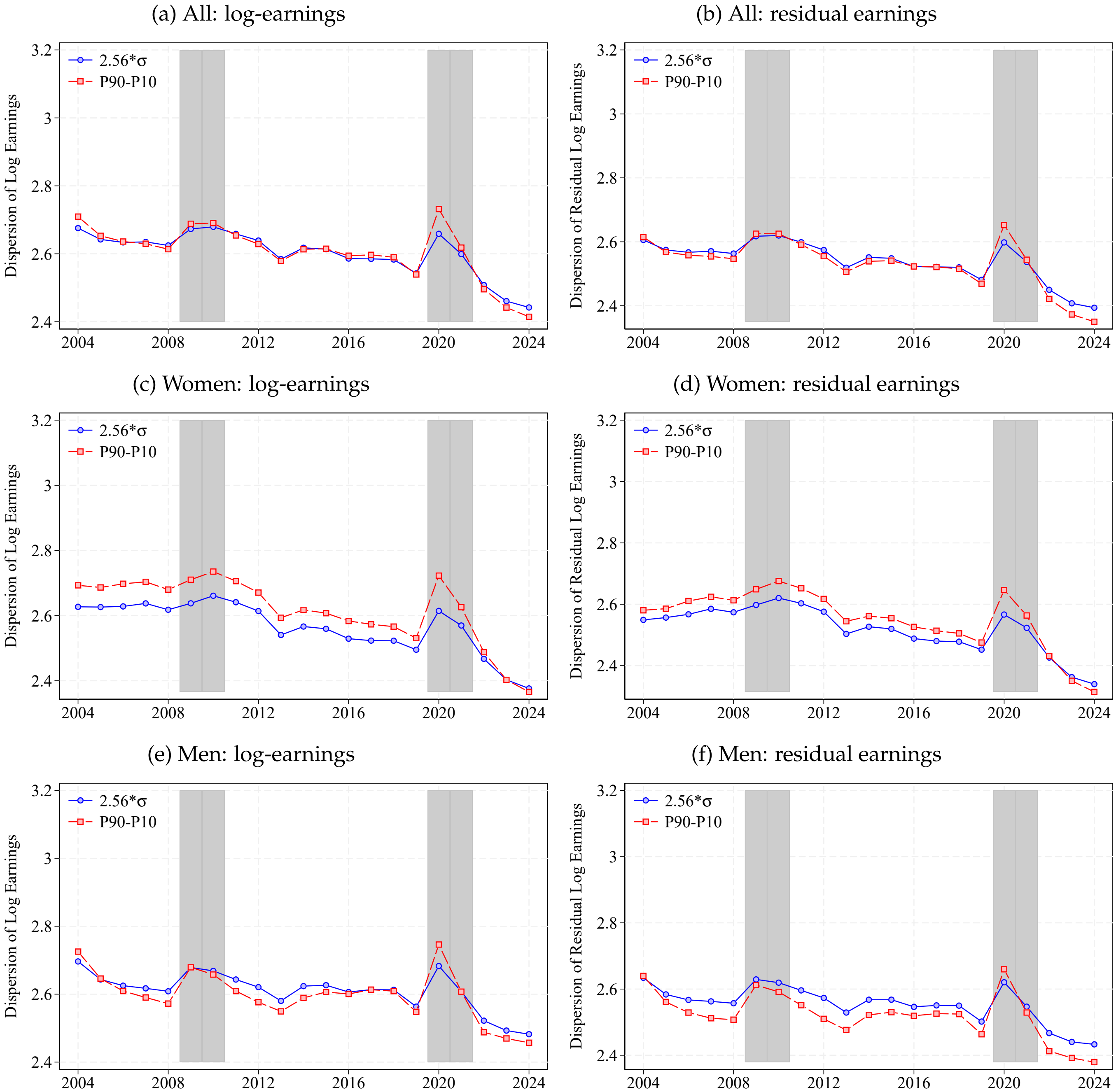
Notes: Figure OA.1 shows the evolution of the following percentiles of log earnings for men and women: P10, P25, P50, P75, P90. Panels (a), (c), and (e) show earnings levels; panels (b), (d), and (f) show the residualized evolution. All percentiles are normalized to 0 in 2004. The gray bars representrecession years, defined as years with an output gap of -0.5 percent or less. Each statistic was obtained with more than 30 individuals.

FIGURE OA.2: Evolution of percentiles of the income distribution with respect to 2004. All workers, women, and men.



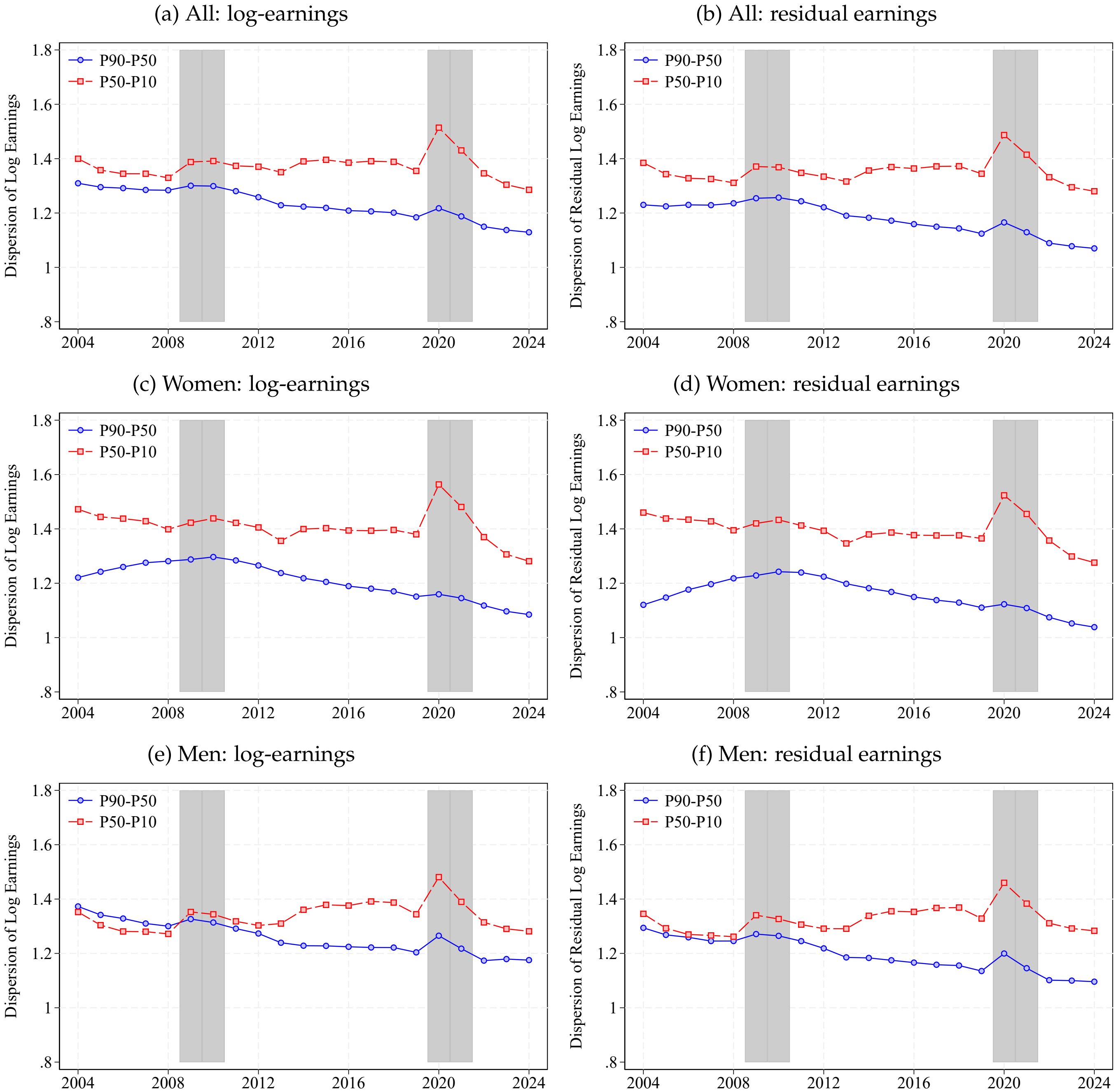
Notes: Figure OA.2 shows the evolution of the following percentiles of log earnings for men and women: P90, P95, P99, P99.9. Panels (a), (c), and (e) show earnings levels; panels (b), (d), and (f) show the residualized evolution. All percentiles are normalized to 0 in 2004. The gray bars representrecession years, defined as years with an output gap of -0.5 percent or less. Each statistic was obtained with more than 30 individuals.

FIGURE OA.3: Dispersion of earnings. All, women, and men.



Notes: Figure OA.3 shows the evolution of dispersion in earnings. Panels (a), (c), and (e) show earnings levels; panels (b), (d), and (f) show residualized earnings. The gray bars representrecession years, defined as years with an output gap of -0.5 percent or less. Each statistic was obtained with more than 30 individuals.

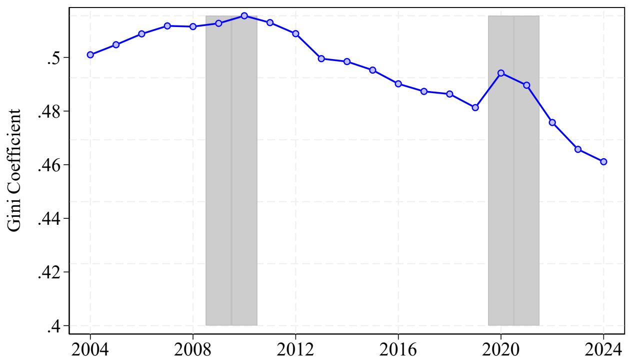
FIGURE OA.4: Dispersion of earnings: evolutions of right and left tails. All, women, and men.



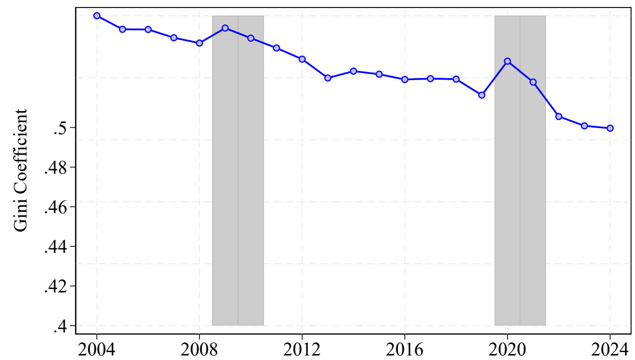
Notes: Figure OA.4 shows the evolution of left and right tail dispersion in earnings. Panels (a), (c), and (e) show earnings levels; panels (b), (d), and (f) show residualized earnings. The gray bars representrecession years, defined as years with an output gap of -0.5 percent or less. Each statistic was obtained with more than 30 individuals.

FIGURE OA.5: Gini Coefficient of labor income

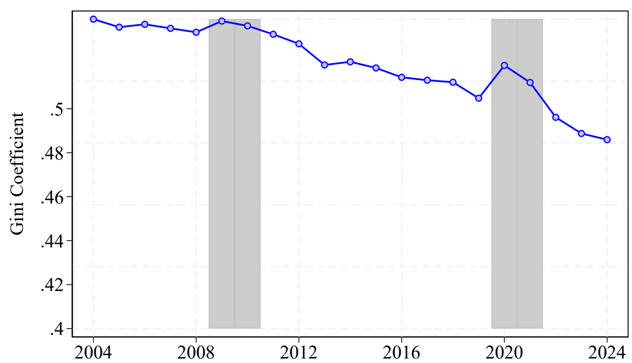
(a) Women



(b) Men



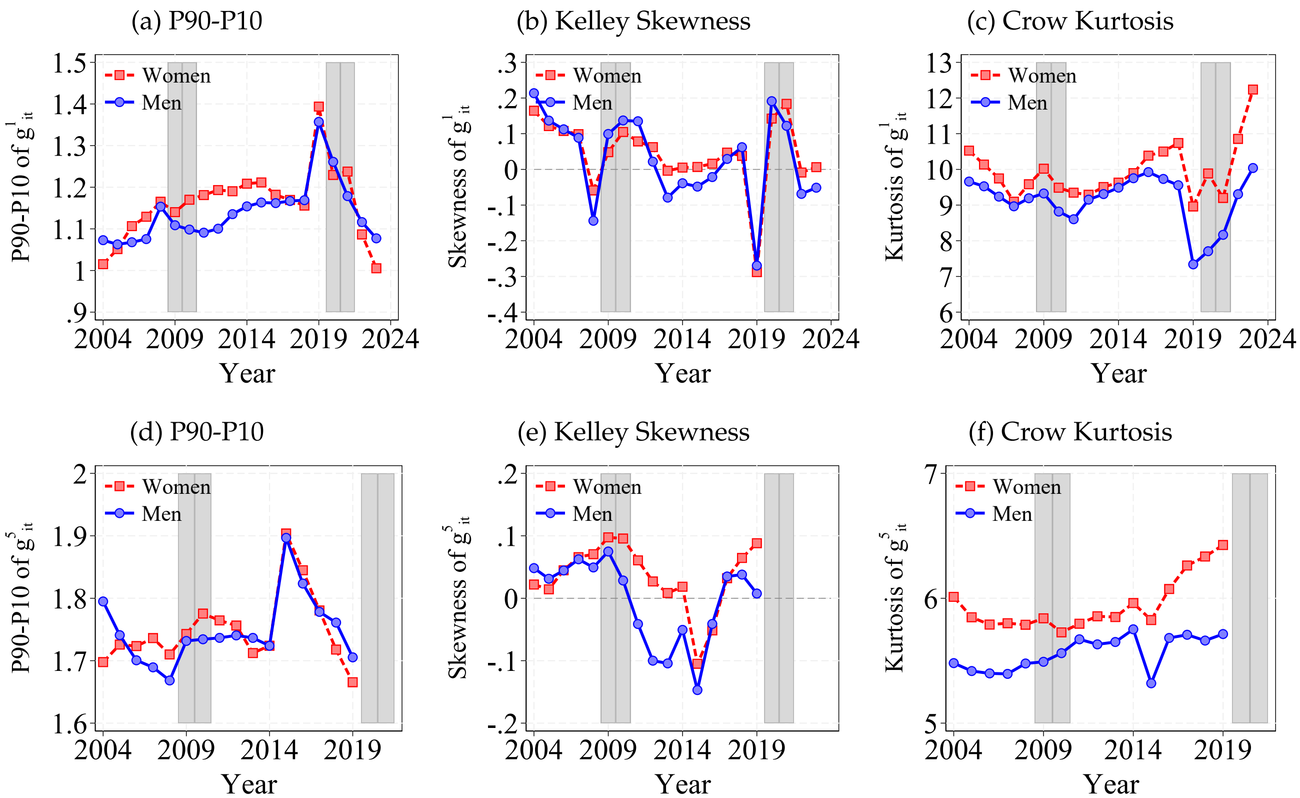
(c) All



Notes: Figure OA.5 shows the evolution of the Gini coefficient for all, men and women. The gray bars represent recession years, defined as years with an output gap of 0.5 percent or less. Each statistic was obtained with more than 30 individuals.

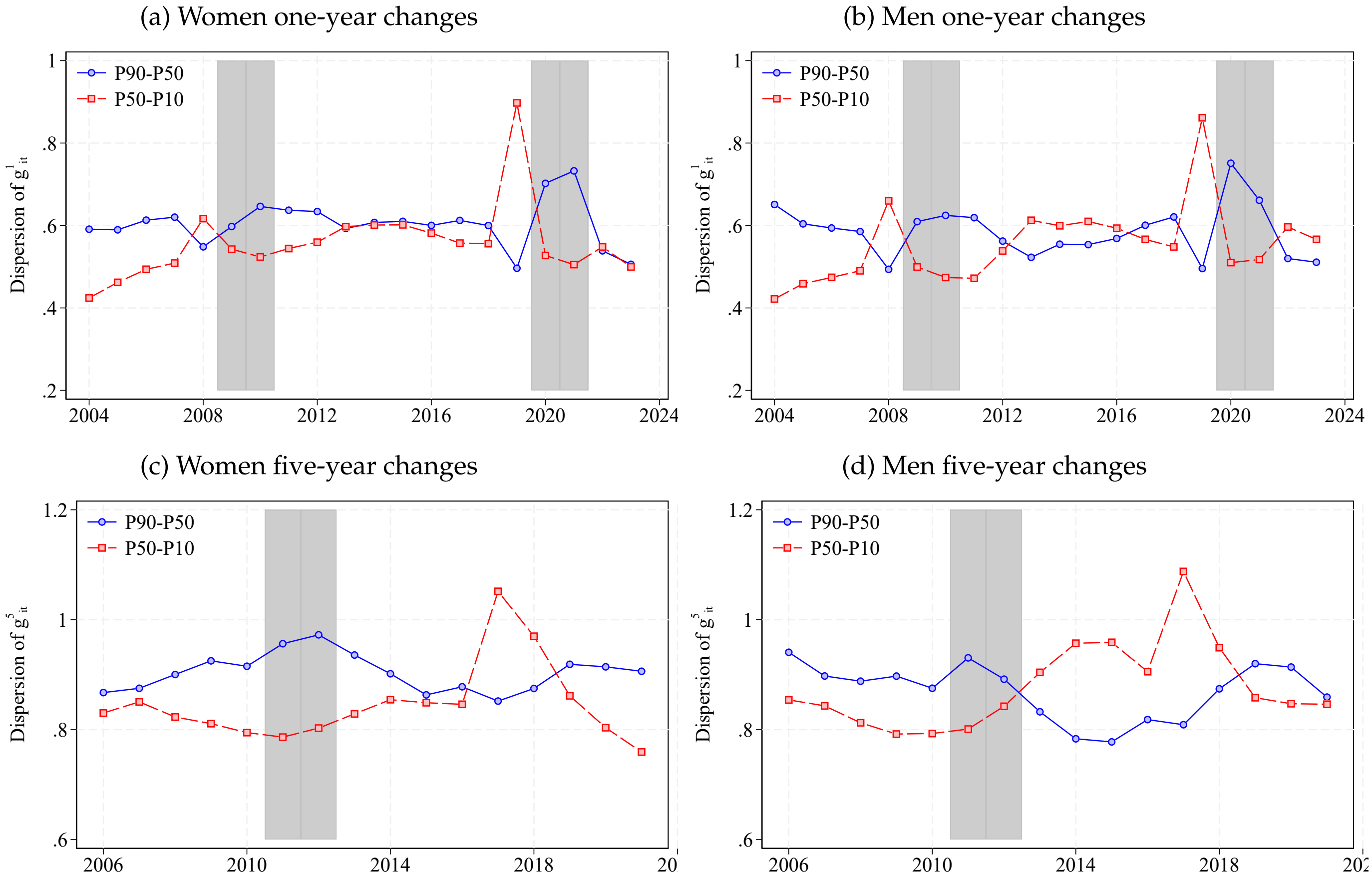
OA.2 Earnings Growth and Income Risk Statistics

FIGURE OA.6: Moments of 1- and 5-year Earnings Growth Distributions.



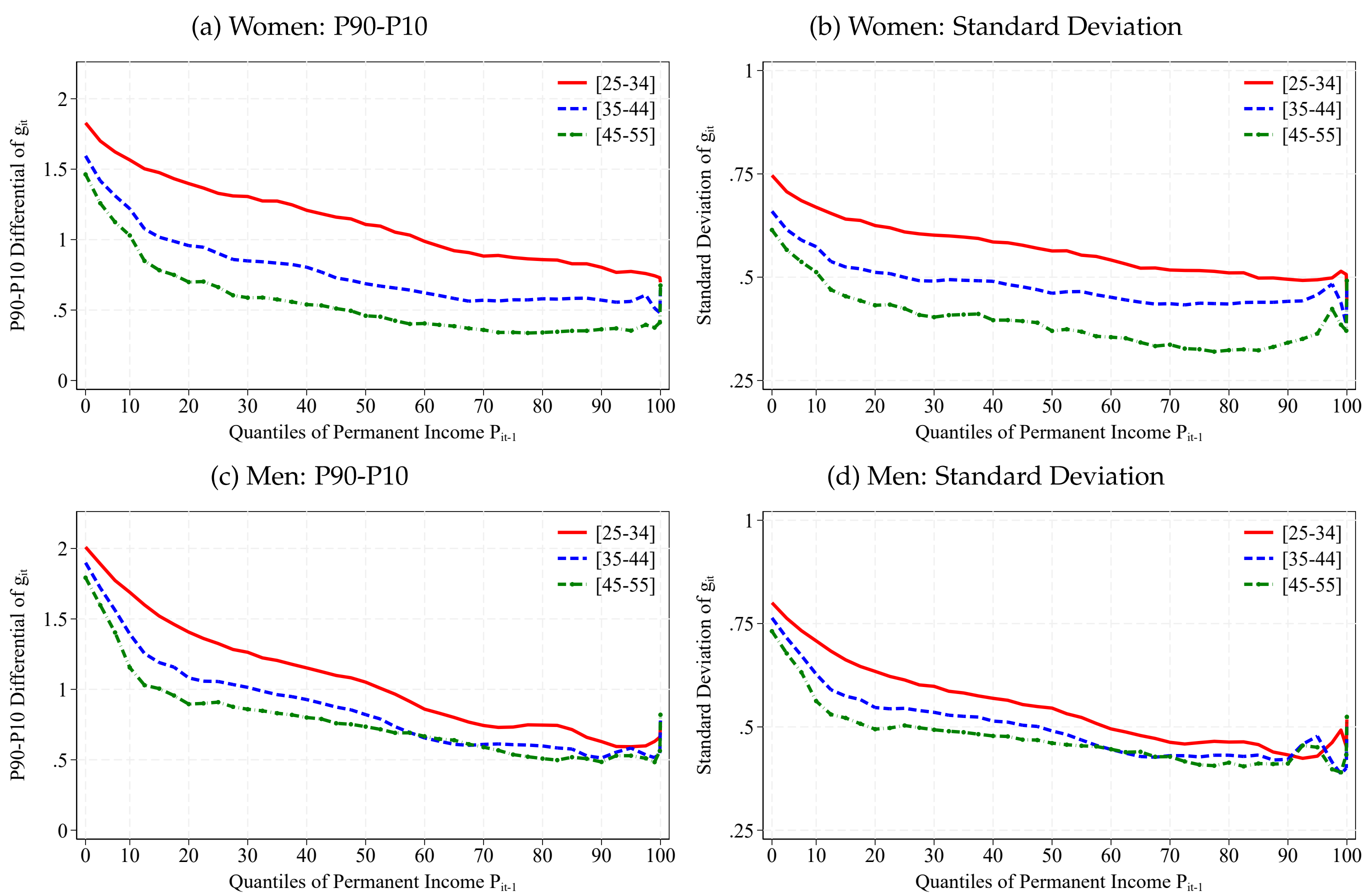
Notes: Figure OA.6 shows the P90-P10, Kelley skewness and excess Crow-Siddiqui kurtosis of 1- and 5-year earnings growth for men and women. The gray bars represent recession years, defined as years with an output gap of 0.5 percent or less. Each statistic was obtained with more than 30 individuals.

FIGURE OA.7: Dispersion of Earnings Growth: Right and Left Tails.



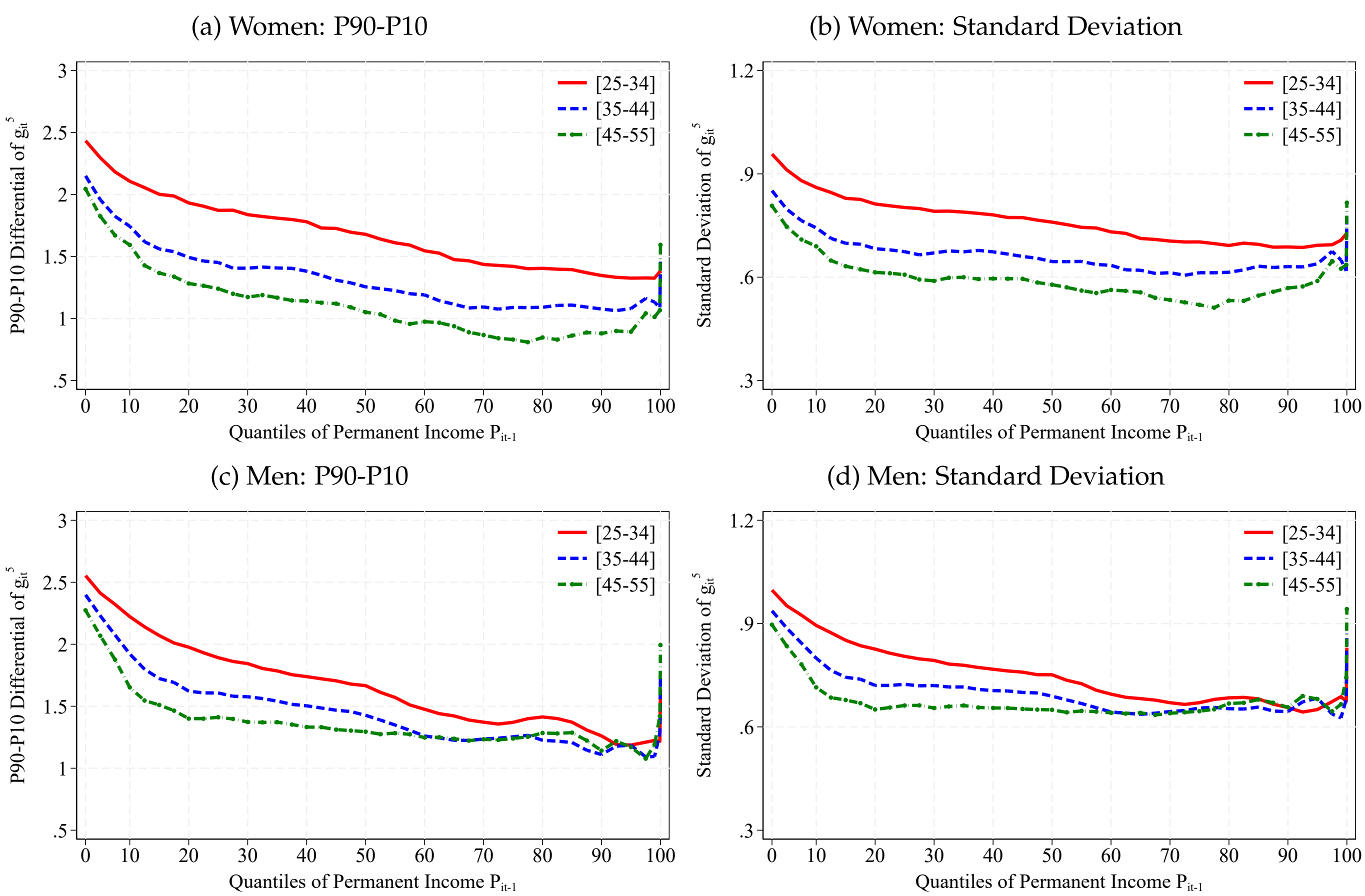
Notes: Figure OA.7 shows the P90-P50 and P50-P10 of 1- and 5-year earnings growth for men and women. The gray bars represent recession years, defined as years with an output gap of 0.5 percent or less. Each statistic was obtained with more than 30 individuals.

FIGURE OA.8: Dispersion of 1-year Earnings Growth by Permanent Earnings and Age.



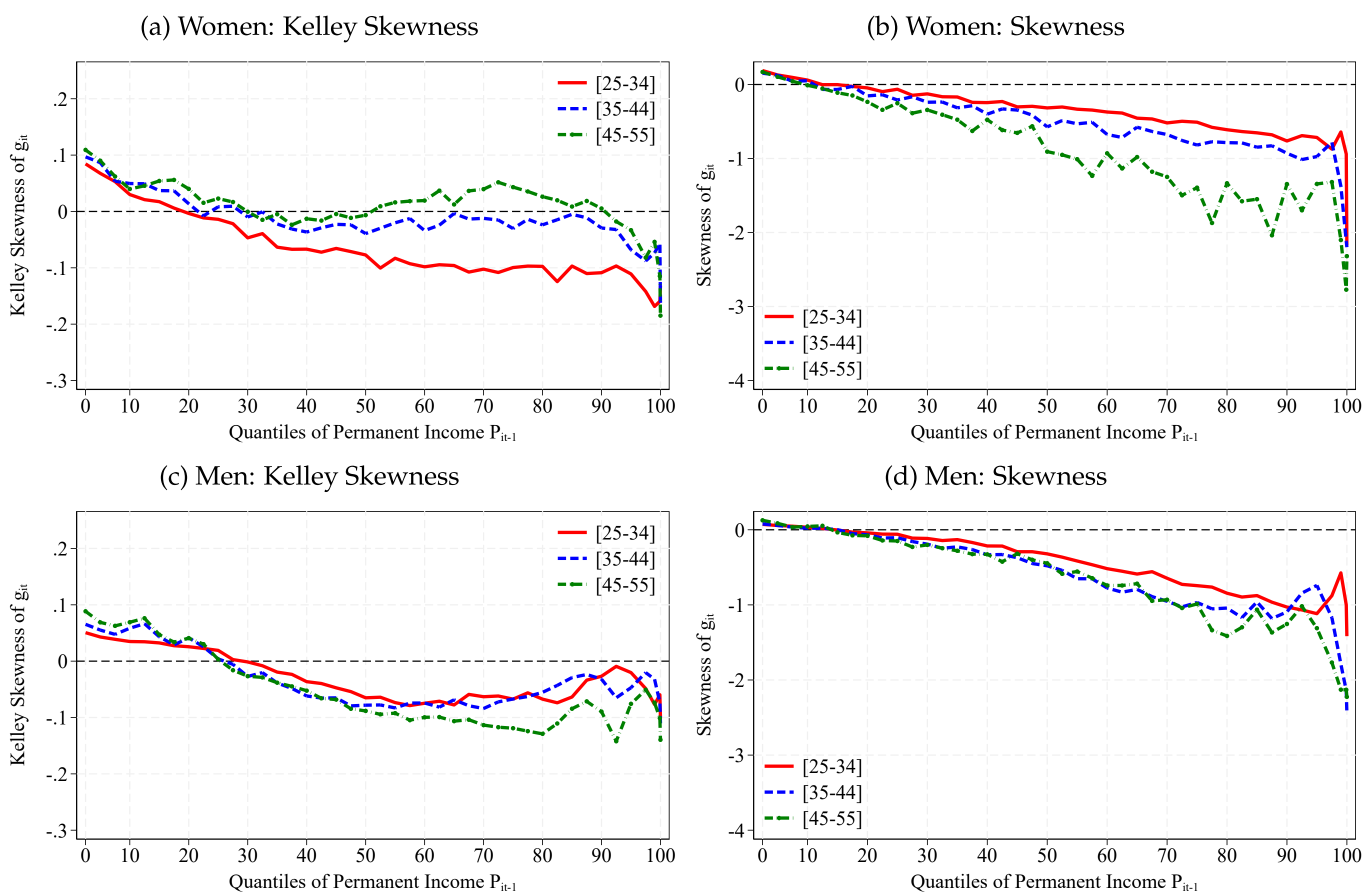
Notes: Figure OA.8 shows the P90-P10 and standard deviation of the 1-year growth rate of residual earnings for men and women within quantiles of the PE distribution, P_{it-1}. The quantiles considered in this plot are every 2.5% until percentile 97.5, we include the 99 percentile and the top 0.1%. The plot shows an average of all years. Each statistic was obtained with more than 30 individuals.

FIGURE OA.9: Dispersion of 5-year Earnings Growth by Permanent Earnings and Age.



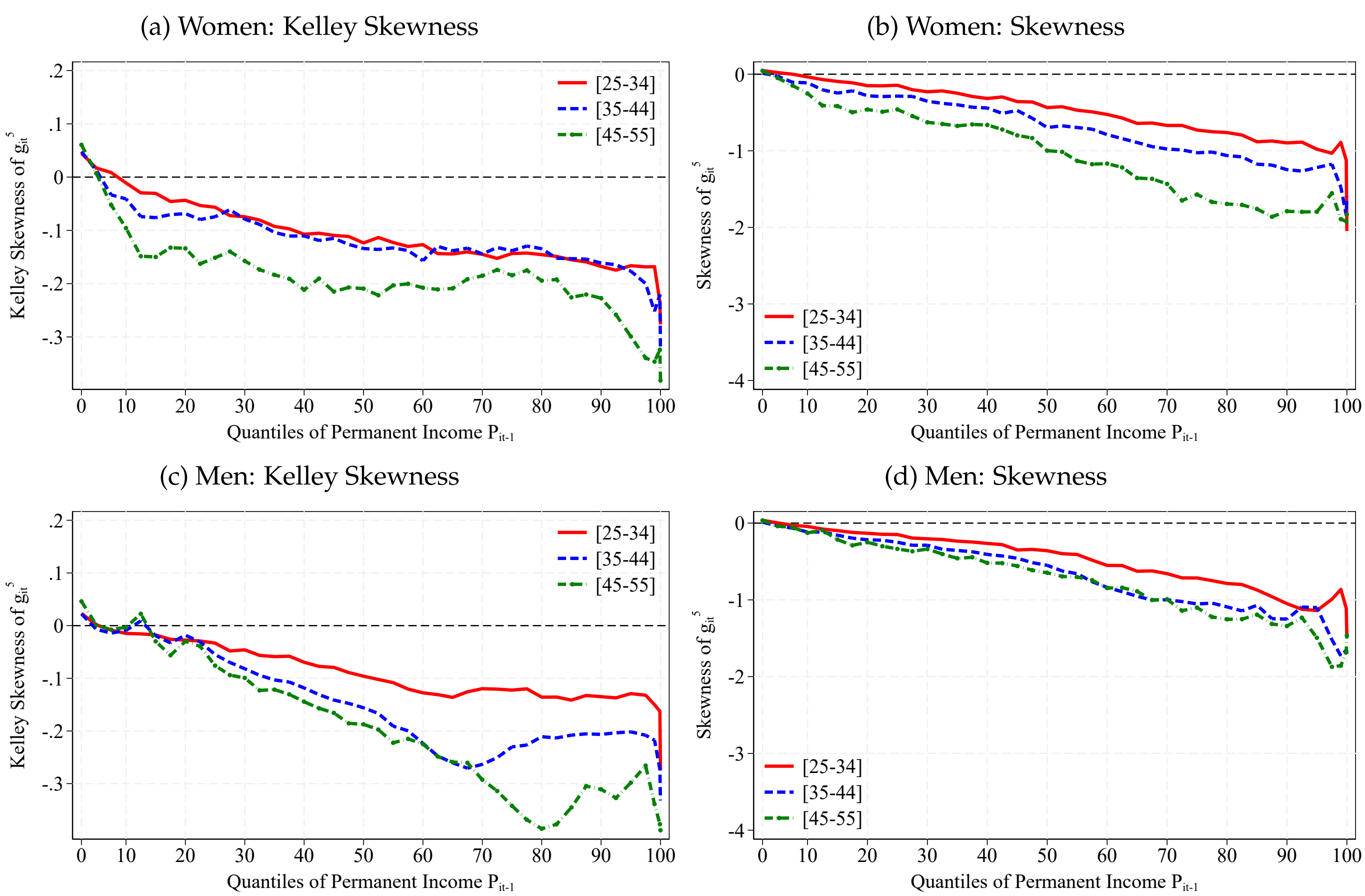
Notes: Figure OA.8 shows the P90-P10 and standard deviation of the 5-year growth rate of residual earnings for men and women within quantiles of the PE distribution, P_{it-1}. The quantiles considered in this plot are every 2.5% until percentile 97.5, we include the 99 percentile and the top 0.1%. The plot shows an average of all years. Each statistic was obtained with more than 30 individuals.

FIGURE OA.10: Skewness of 1-year Earnings Growth by Permanent Earnings and Age.



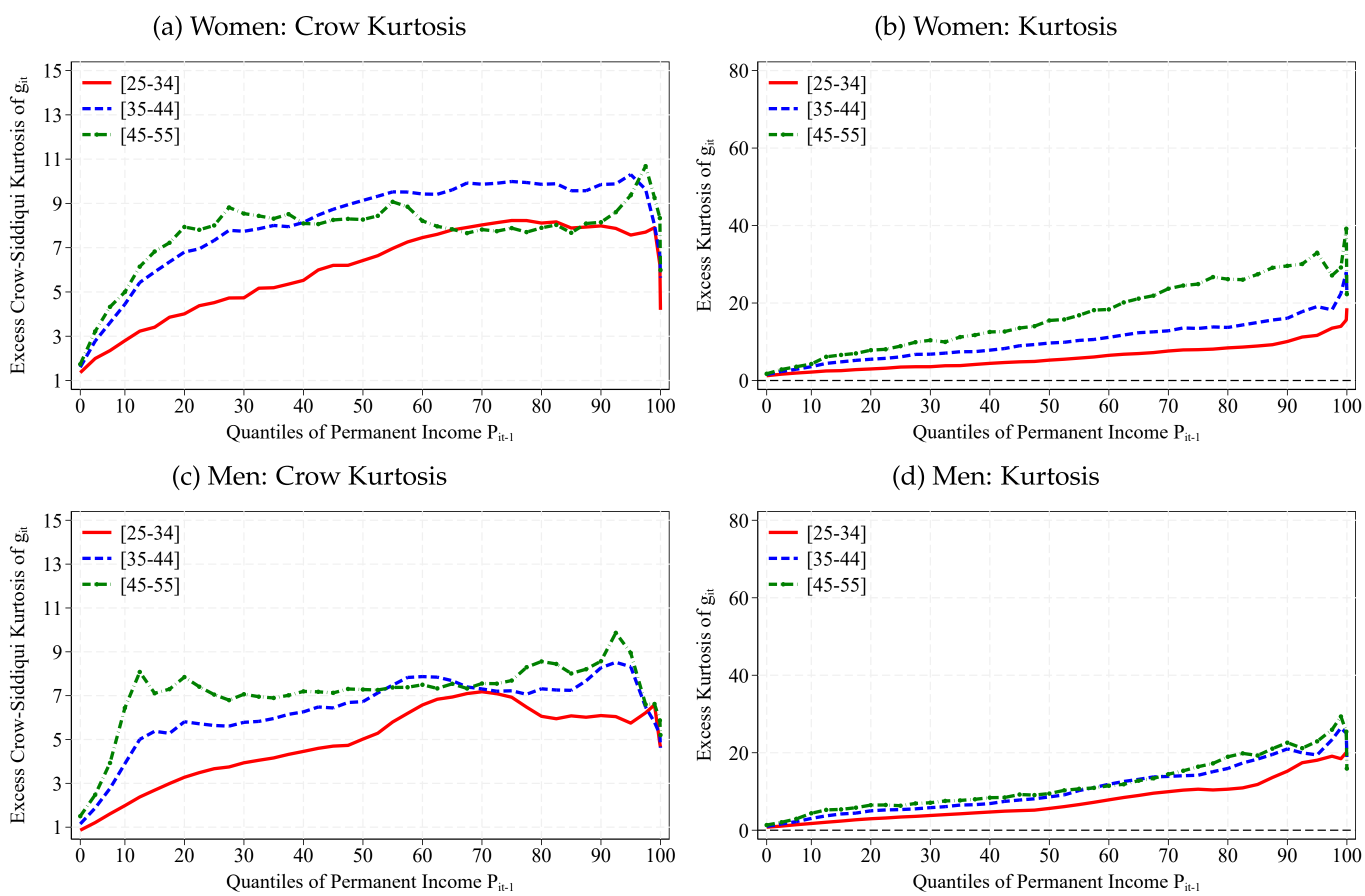
Notes: Figure OA.10 shows the Kelley skewness and the skewness of the 1-year growth rate of residual earnings for men and women within quantiles of the PE distribution, P_{it-1}. The quantiles considered in this plot are every 2.5% until percentile 97.5, we include the 99 percentile and the top 0.1%. The plot shows an average of all years. Each statistic was obtained with more than 30 individuals.

FIGURE OA.11: Skewness of 5-year Earnings Growth by Permanent Earnings and Age.



Notes: Figure OA.11 shows the Kelley skewness and the skewness of the 5-year growth rate of residual earnings for men and women within quantiles of the PE distribution, P_{it-1}. The quantiles considered in this plot are every 2.5% until percentile 97.5, we include the 99 percentile and the top 0.1%. The plot shows an average of all years. Each statistic was obtained with more than 30 individuals.

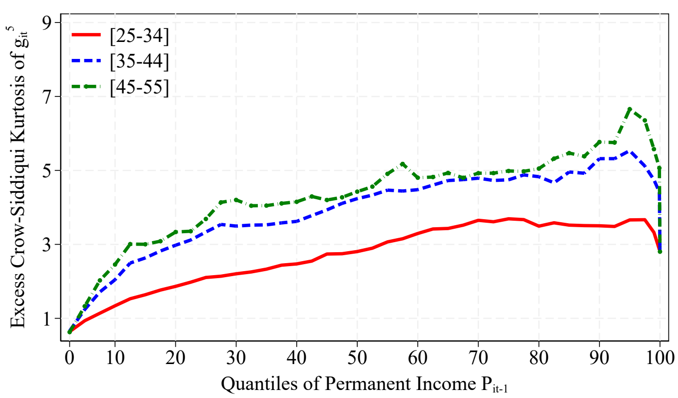
FIGURE OA.12: Kurtosis of 1-year Earnings Growth by Permanent Earnings and Age.



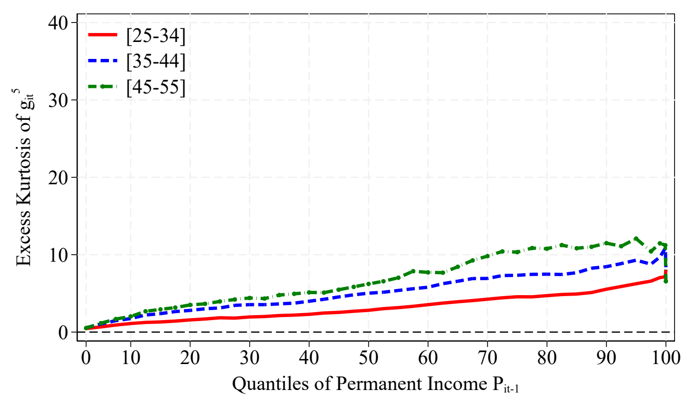
Notes: Figure OA.12 shows the Crow kurtosis and kurtosis of the 1-year growth rate of residual earnings for men and women within quantiles of the PE distribution, P_{it-1}. The quantiles considered in this plot are every 2.5% until percentile 97.5, we include the 99 percentile and the top 0.1%. The plot shows an average of all years. Each statistic was obtained with more than 30 individuals.

FIGURE OA.13: Kurtosis of 5-year Earnings Growth by Permanent Earnings and Age.

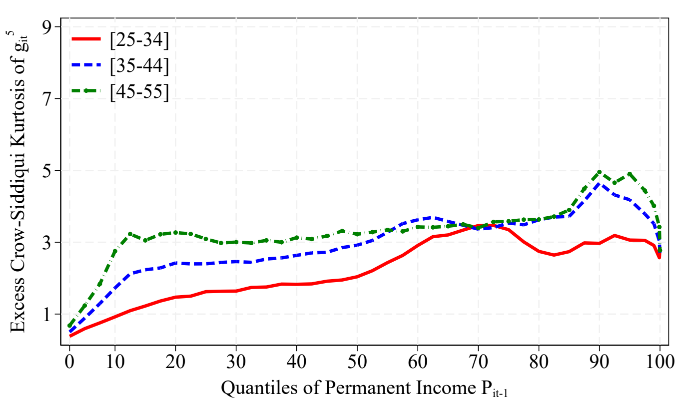
(a) Women: Crow Kurtosis



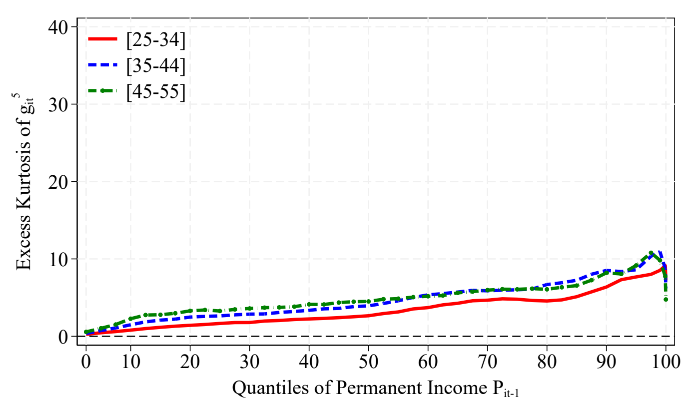
(b) Women: Kurtosis



(c) Men: Crow Kurtosis



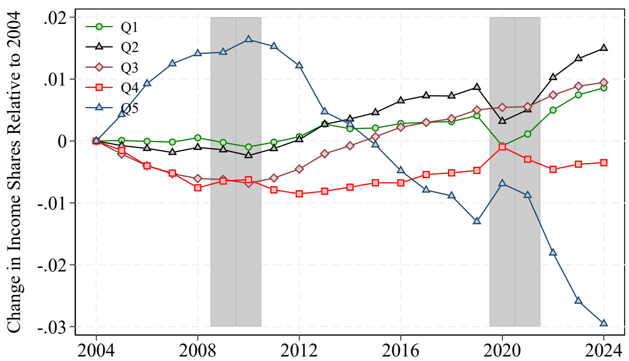
(d) Men: Kurtosis



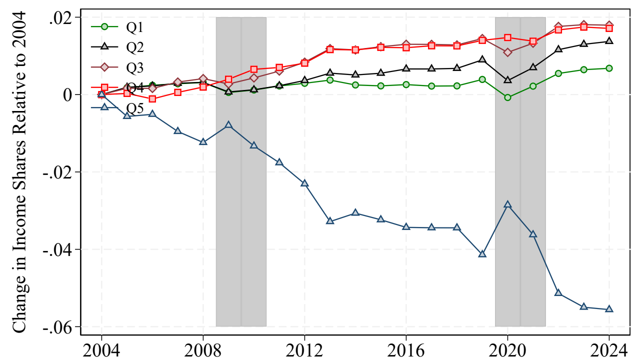
Notes: Figure OA.13 shows the Crow kurtosis and kurtosis of the 5-year growth rate of residual earnings for men and women within quantiles of the PE distribution, P_{it-1}. The quantiles considered in this plot are every 2.5% until percentile 97.5, we include the 99 percentile and the top 0.1%. The plot shows an average of all years. Each statistic was obtained with more than 30 individuals.

FIGURE OA.14: Evolution of income shares. Different quintiles.

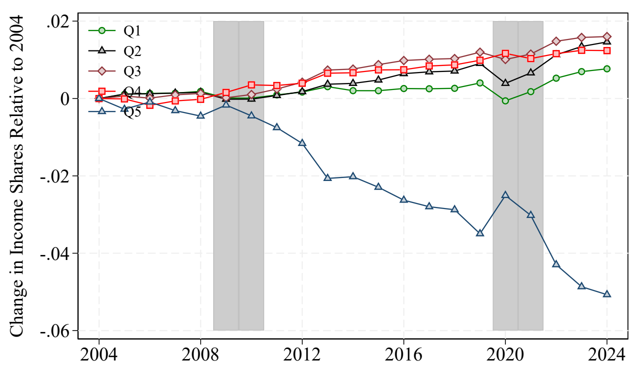
(a) Women



(b) Men

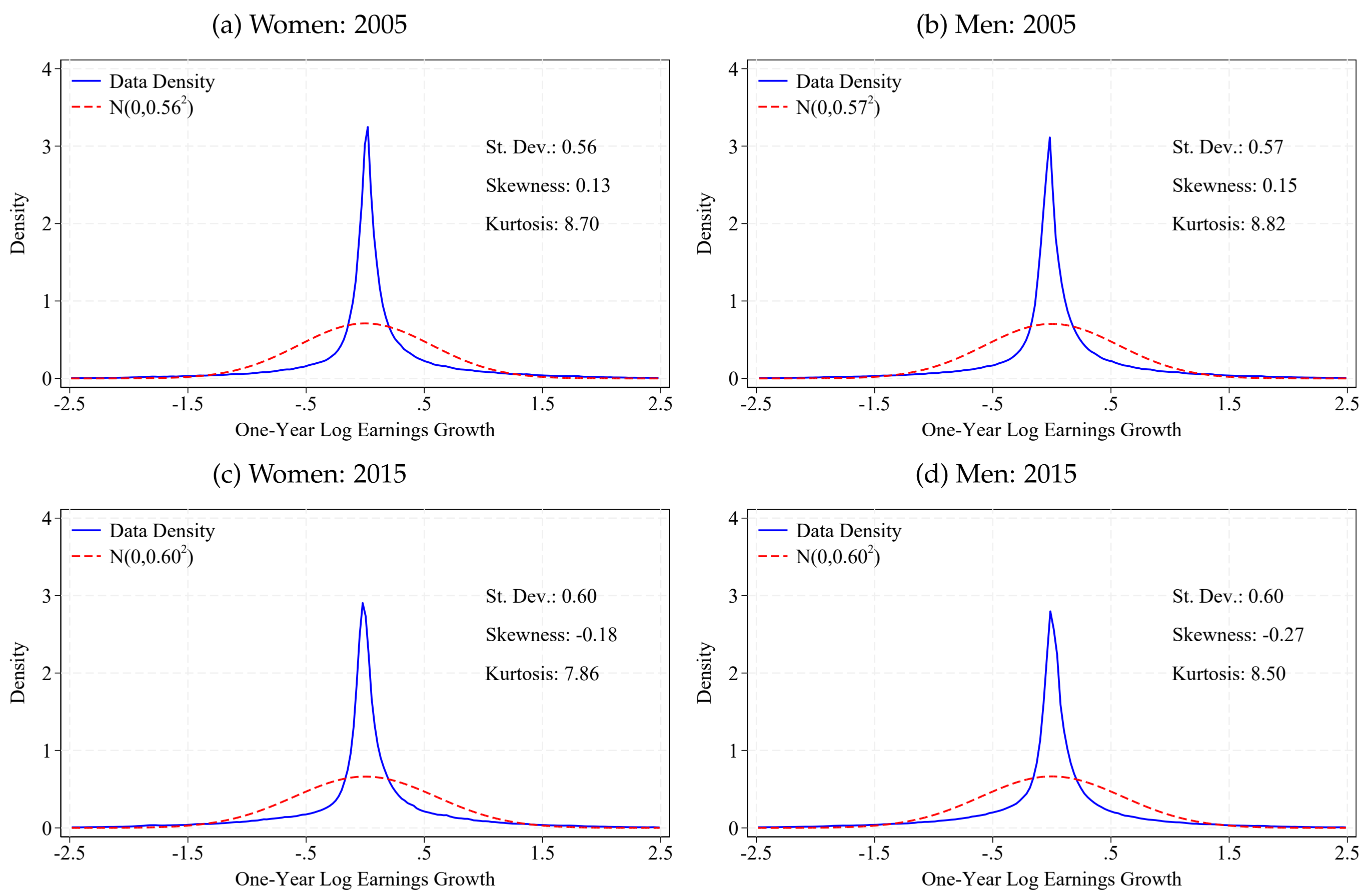


(c) All



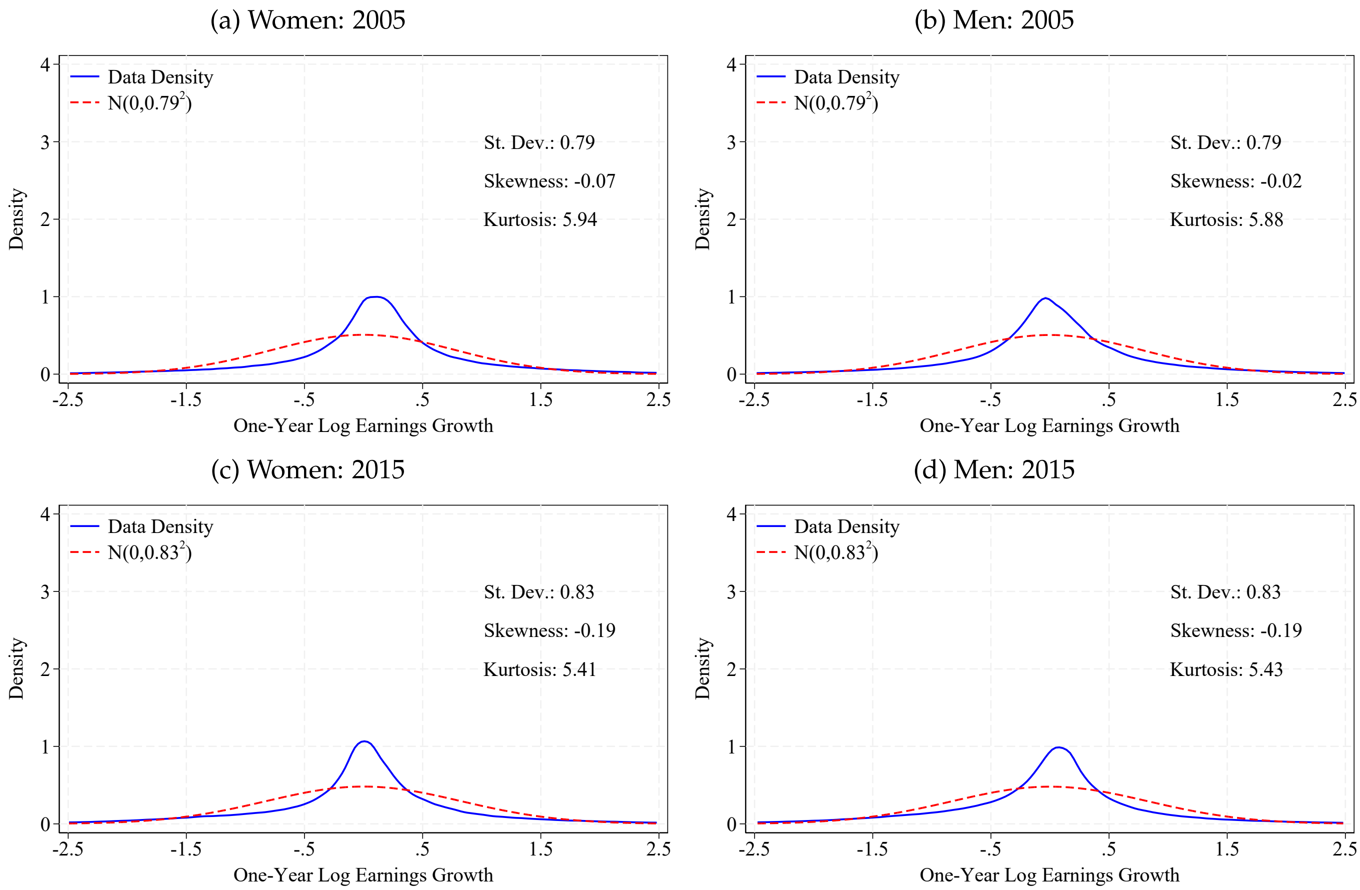
Notes: Figure OA.14 shows the evolution income shares by quintile for all, women and men: bottom 50, and top 10, 5, 1, 0.5, 0.1, and 0.01 percent. The gray bars represent recession years, defined as years with an output gap of 0.5 percent or less. Each statistic was obtained with more than 30 individuals.

FIGURE OA.15: Distribution of 1-year of earnings growth.



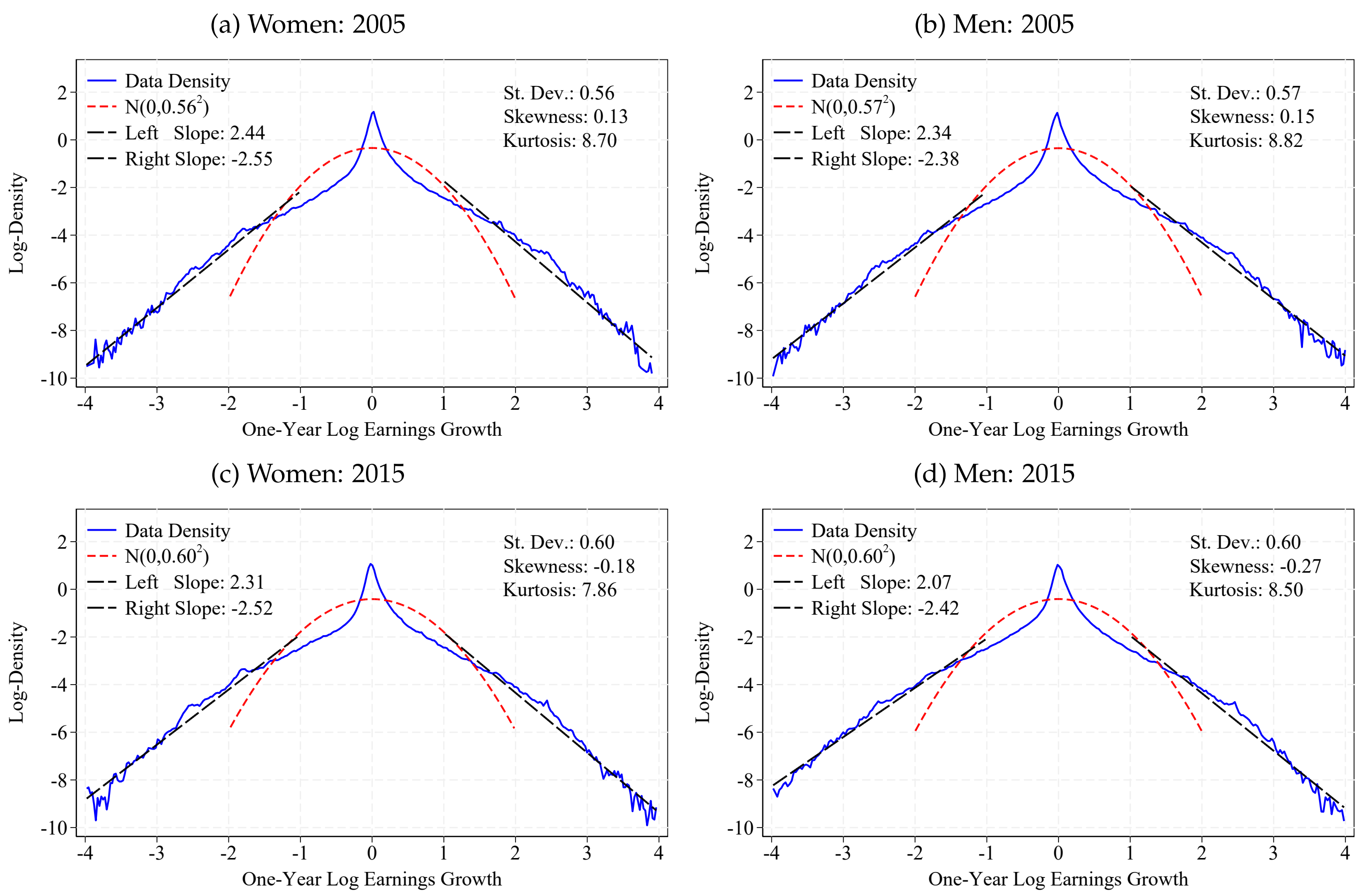
Notes: Figure OA.15 shows Empirical density of 1-year log earnings change and corresponding cross-sectional moments for men and women in 2005 and 2015. See Section 2 for sample selection and definitions. Each statistic was obtained with more than 30 individuals.

FIGURE OA.16: Distribution of 5-year of earnings growth.



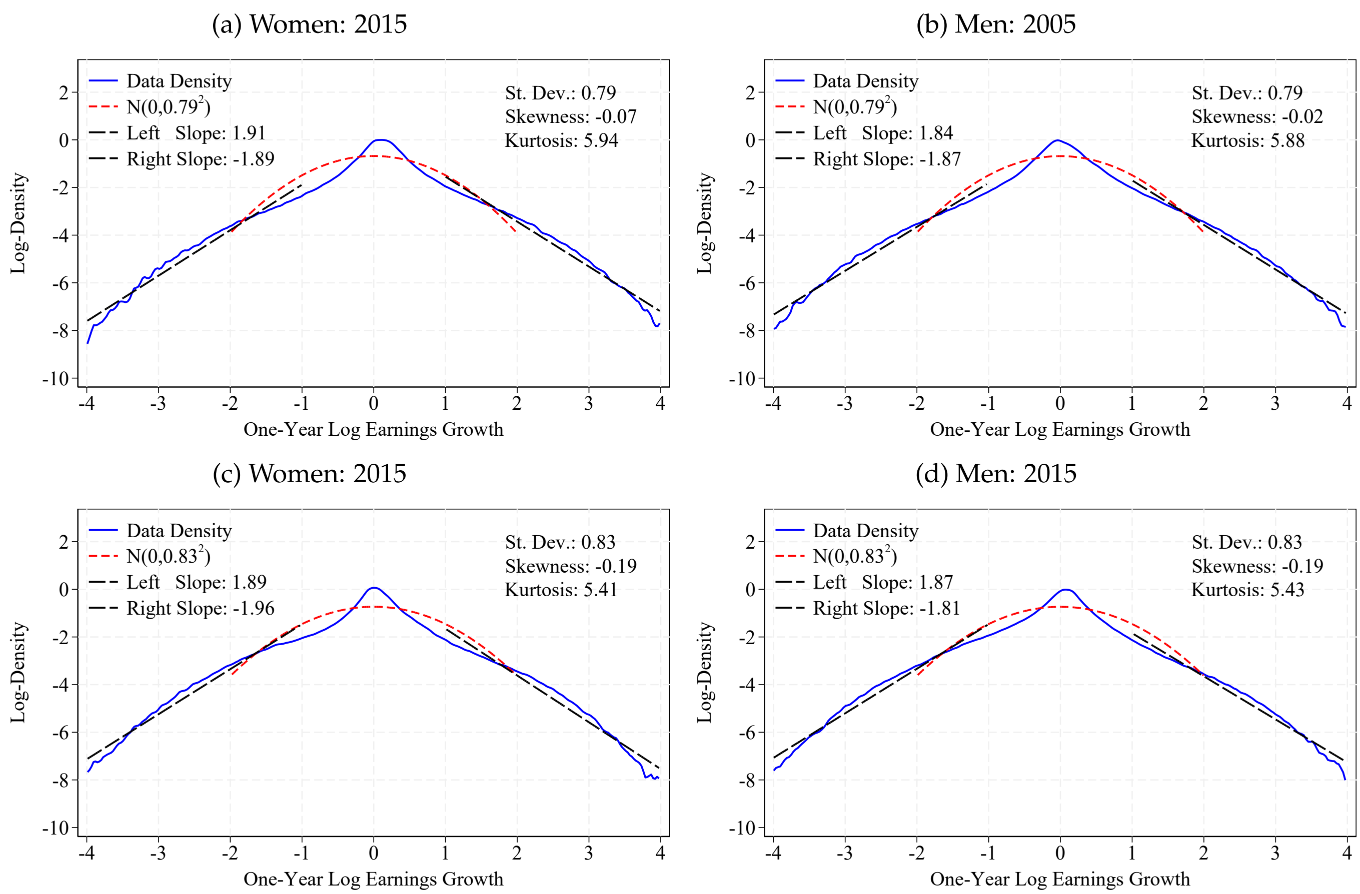
Notes: Figure OA.15 shows Empirical density of 5-year log earnings change and corresponding cross-sectional moments for men and women in 2005 and 2015. See Section 2 for sample selection and definitions. Each statistic was obtained with more than 30 individuals.

FIGURE OA.17: Log-density of 1-year earnings growth.



Notes: Figure OA.17 shows Empirical log-density of 1-year log earnings change and corresponding cross-sectional moments for men and women in 2005 and 2015. See Section 2 for sample selection and definitions. Each statistic was obtained with more than 30 individuals.

FIGURE OA.18: Log-density of 5-year earnings growth.



Notes: Figure OA.15 shows Empirical log-density of 5-year log earnings change and corresponding cross-sectional moments for men and women in 2005 and 2015. See Section 2 for sample selection and definitions. Each statistic was obtained with more than 30 individuals.

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