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Earnings Inequality and Risk over Two Decades of Economic Development in Lithuania*

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ABSTRACT

Using Social Security records between 2000 and 2020, we provide a comprehensive analysis of labor earnings inequality and its dynamics over the course of Lithuania's economic development. Since 2000, there has been a substantial decline in earnings inequality, largely driven by the rapid growth of earnings at the bottom of the distribution, while earnings volatility has hardly changed. Importantly, we estimate a relatively high sensitivity of earnings growth to changes in real GDP, which declines with the level of permanent income. Additionally, we find that the idiosyncratic earnings risk of individuals at the bottom of the permanent income distribution is less sensitive to aggregate growth than that of individuals in the top half. Taken together, our findings underscore that analyzing earnings risk is critical to properly understanding the dynamics of inequality and designing effective policies to address it.

Keywords: Income inequality, income risk, income mobility, administrative data

JEL Codes: D31, E24, J31

1 Introduction

How work is rewarded determines the well-being of most people around the world. Not surprisingly, income inequality has been and continues to be a central issue for scholars, policymakers, and the general public. Discussions typically revolve around measures of cross-sectional inequality, which provide only a snapshot of the degree of earnings dispersion. However, in formulating policies to address prevailing inequality, it is equally important to understand how inequality evolves over time and over the life cycle, the persistence of (initial) differences, and the degree of uncertainty and variability (risk) in earnings faced by individuals. Similarly, how earnings dynamics differ across individuals and evolve with aggregate fluctuations is crucial both for understanding the distributional and welfare consequences of macroeconomic shocks and for designing stabilization policies that prevent cyclical increases in inequality from becoming permanent.

As part of the second wave of the Global Repository of Income Dynamics (GRID) project, this paper studies labor income inequality, risk, and mobility in Lithuania from 2000 to 2020. Lithuania provides an interesting case study for characterizing earnings inequality and volatility for several reasons. Starting in 1991, the country underwent a dramatic economic transformation, moving from a centrally planned economy to a market economy. Throughout our period of analysis, this structural transformation resulted in the economy more than doubling in real terms and becoming a high-income country. Over its development process, Lithuania has been among the most unequal countries in terms of labor income in the EU (OECD, 2011; Černiauskas et al., 2022). The government has relied heavily on minimum wage increases as the primary policy tool to tackle this inequality (Magda et al., 2021; Garcia-Louzao and Tarasonis, 2023b; Černiauskas and Garcia-Louzao, 2024). Finally, the recently available Social Security records allow a novel and comprehensive view of the dynamics of labor income inequality and volatility over these two decades of development, which were temporarily interrupted by the Great Recession of 2008, when the economy collapsed relatively more than most developed economies but also recovered faster (Garcia-Louzao and Tarasonis, 2023a).

We begin by documenting several facts about earnings inequality and the dynamic properties of earnings volatility and mobility. To this end, we compute standardized measures following the GRID convention, using two decades of Social Security data. Our analysis shows that there has been substantial real earnings growth for both men and women across all segments of the earnings distribution. However, earnings at the bottom have grown disproportionately more than those at the top. As a result, both between and within cohorts, earnings inequality in Lithuania declined significantly between 2000 and 2020. Notably, this steady decline was temporarily interrupted during the Great Recession, when earnings fell the most at the bottom of the distribution.

The dynamics of individual earnings risk, i.e., the volatility of earnings changes, paint a somewhat different picture. While the dispersion of earnings risk faced by Lithuanian workers is higher than in more advanced European countries, its evolution between 2000 and 2020 is relatively stable, except for the Great Recession. During the economic crisis, earnings volatility showed opposite cyclicality on two sides of the distribution: shocks increased for those in the bottom half of the distribution, while they became less pronounced for those at the top. We also show that the distribution of earnings changes is significantly non-normal, with non-zero skewness and a pronounced central tendency.

Finally, we characterize how individual workers' positions in the income distribution evolve over time. Pooling the data over all years, we find that the level of income mobility in Lithuania is higher than in most countries in the first wave of GRID and, if anything, comparable to that in the Nordic countries. We also document that income mobility was relatively stable between 2000 and 2020 and that the mobility of young workers, especially women, is significantly higher than that of older workers.

To relate the earnings dynamics of Lithuanian workers documented in the first part of the paper to GDP growth, in a second step, we estimate the so-called GDP betas following the econometric approach of Guvenen et al. (2017) and Busch et al. (2022). We find that a contemporaneous 1% increase in real GDP is correlated with an average real annual earnings growth of 1.3% for men, while the figure is 0.7% for women. Interestingly, we find a negative and statistically significant correlation between GDP growth and earnings risk for men but not for women.

Higher orders of the distribution of earnings changes are positively correlated with GDP growth for both men and women, but the sensitivity is higher for the former. However, there is relevant heterogeneity in the correlation of earnings growth and risk with GDP growth. In particular, we find that the position of workers in the permanent income distribution matters: while the sensitivity of earnings growth to changes in real GDP declines with the level of permanent income, individual earnings risk of individuals at the bottom of the distribution appears to be less sensitive (or not at all responsive) to aggregate economic growth. Interestingly, we document little evidence of age heterogeneity, except for women under 35, who show some differences relative to the rest of the workforce, plausibly related to childbearing.

Our paper connects with a large body of empirical research documenting the level and dynamics of labor income inequality within and across countries (see Hoffmann et al., 2022; Guvenen et al., 2022; Banks et al., 2024, for some of the most recent studies comparing different countries). Although the analysis of inequality in Lithuania is not new, e.g., Magda et al. (2021); Černiauskas et al. (2022); Garcia-Louzao and Ruggieri (2023); or Černiauskas and Garcia-Louzao (2024), we complement this line of work by providing a comprehensive description of earnings inequality, risk, and mobility over two decades. In this respect, we can place Lithuania internationally using comparable data and methods within the GRID project and document how earnings inequality and risk evolve over time within a country rather than relying on cross-country data. In doing so, we, for the first time in Lithuania, (i) characterize the dynamic properties of earnings volatility, (ii) estimate its sensitivity to aggregate economic growth, and (iii) explore its heterogeneity along the income distribution. In doing so, we also add to recent literature that has focused on individual earnings risk and its co-movement with aggregate fluctuations (e.g., Guvenen et al., 2014; Busch et al., 2022).

The rest of the paper is organized as follows. Section 2 characterizes the Lithuanian economy and describes the data. Section 3 discusses the set of moments that characterize earnings inequality, volatility, and mobility, while Section 4 estimates the correlation between these moments and GDP growth. Section 5 concludes.

2 Data and institutional context

2.1 The Lithuanian economy between 2000 and 2020

During the period under study, Lithuania became a member of the World Trade Organization in 2001, which initiated a critical phase of opening up the economy to international markets. In 2004, Lithuania joined the European Union, which had significant political, economic, and social consequences for the country. Accession was crucial for the country's development, as it received generous EU funds to develop infrastructure and implement economic and social policies. Accession to the EU also impacted democracy and governance, as the country had to meet EU standards, as well as providing access to new trading partners and the attraction of significant foreign investment (Randveer and Staehr, 2021). Joining the EU also introduced the free movement of capital and labor. While access to capital was crucial to support economic growth, the right to live and work in other EU member states led to a wave of mass emigration (Klüsener et al., 2015). For example, after Lithuania joined the EU, more than 5% of the Lithuanian working-age population resided in a European country by 2009 (Fic et al., 2011).

In Figure 1, we provide graphical evidence on the evolution of key macroeconomic indicators to characterize the extraordinary development of the Lithuanian economy. Panel A shows that the Lithuanian economy more than doubled in real terms between 2000 and 2020, moving from a middle-low-income country to a high-income country, according to the World Bank. However, during this period of long-term economic growth, the country was also hit hard by the Great Recession, with GDP falling sharply between 2008 and 2009. Still, it also showed a rapid recovery compared to other economies. Notably, productivity declined less than GDP, partly due to labor reallocation from less to more productive firms (Garcia-Louzao and Tarasonis, 2023a). Panel B illustrates international trade's critical role in the Lithuanian economy, as exports and imports account for about 70% of the GDP. Panel C reports two standard measures in the economic growth literature: convergence, measured as the log difference in GDP per capita between the OECD countries and Lithuania, and catching-up, measured as the ratio of Lithuania's GDP per capita to the same ratio for the OECD, both GDP measures expressed in 2010 US dollars. The figure clearly shows that the process of convergence experienced by the Lithuanian economy is well underway. For example, looking at specific OECD countries, Lithuania's GDP per capita in 2019 was 28% of that in the US, 40% of Germany's, 80% of Portugal's, or 168% of Mexico's.

Alongside the macroeconomic developments described above, there have also been several labor market reforms that might have had an impact on earnings dynamics.

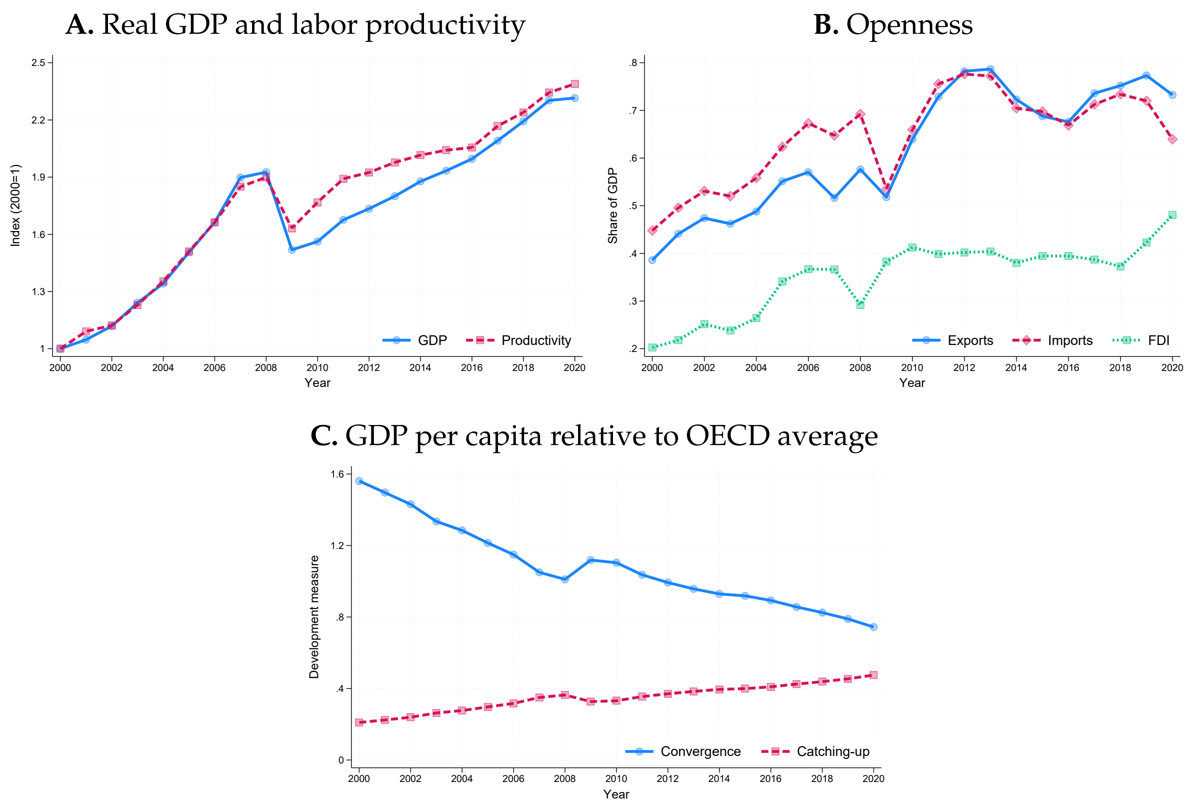


Figure 1: Macroeconomic developments in Lithuania between 2000 and 2020. *Note*: Real GDP and labor productivity (gross value added per worker) normalized to their value in 2000. Convergence is the log difference in GDP per capita (expressed in 2010 US dollars) between the OECD and Lithuania, while catching-up is the ratio of real GDP per capita in Lithuania to that in the OECD. *Source*: Panels A and B, Statistics Lithuania and own calculations; Panel C, St. Louis FRED and own calculations.

Between 2000 and 2020, the nominal minimum wage increased 16 times, from 160 to 607 euros, or 380% (235% in real terms). In addition to the minimum wage policy, the government modified the old industrial relations system to introduce more flexibility for companies and more worker protection. On the one hand, a New Labor Code was introduced, which reduced statutory severance pay and simplified hiring and firing procedures. The new Labor Code also indirectly affected the minimum wage level by preventing employers from paying the minimum wage to skilled workers. On the other hand, a new unemployment insurance law was enacted to replace the previous (and first) law introduced in 2005. This new legislation made the system more generous by relaxing eligibility criteria and increasing the duration and level of benefits.

Figure 2 shows the evolution of key labor market statistics. Panel A focuses on the dynamics of the working-age population together with employment and firms. The figure illustrates the massive decline in the labor force since 2000, which accelerated

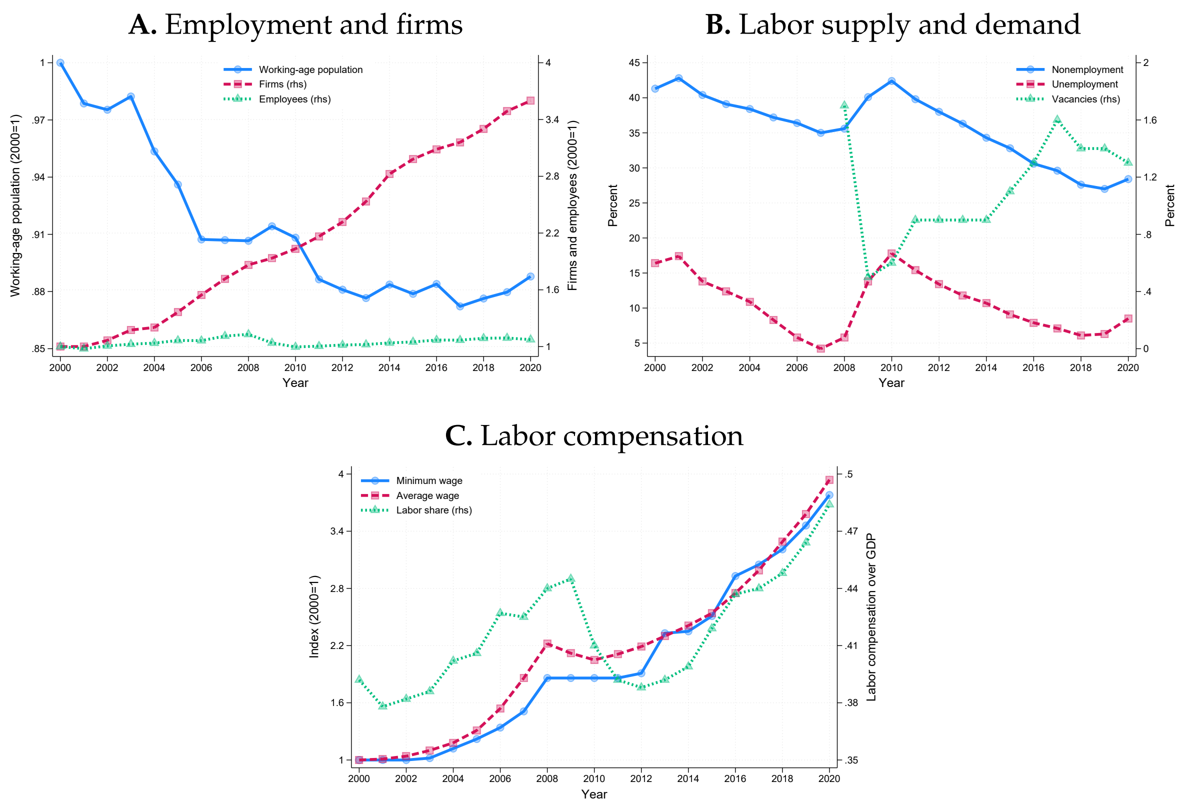


Figure 2: Labor market trends in Lithuania between 2000 and 2020. *Note*: Working-age population, employment, firms, wages, and the minimum wage are normalized to their value in 2000. *Source*: Statistics Lithuania and own calculations.

in 2004 when Lithuania joined the European Union. In addition, it reveals the striking expansion of the number of firms, mirroring the dynamics of economic growth. Over the same period, employment also increased by about 10% relative to its initial level in 2000. Panel B provides statistics highlighting the tightening of the labor market, with the unemployment rate reaching historically low levels before the COVID-19 shock.[1] Panel C shows that the (nominal) average wage was five times higher in 2020 than in 2000. The figure also reveals that the minimum wage experienced a similar expansion. Importantly, the significant decline in labor supply, along with the increase in the number of firms and, thus, the demand for labor, led to substantial labor shortages that also had implications for wages. Such labor market dynamics have favored workers relative to firms (or capital), as suggested by the increase in the labor share and supported by evidence of the declining labor market power of firms in Lithuania (Garcia-Louzao and Ruggieri, 2023; Ding et al., 2025).

[1]The impact of the pandemic on the labor market was not as severe in Lithuania compared to other economies (Garcia-Louzao and Vėlyvis, 2021).

2.2 Social Security records

Our main data source is a 25 percent "de facto random" sample of individuals who were in the Social Security system at any time between 2000 and 2020.[2] The dataset has a longitudinal design with unique identifiers for each individual, who are followed on a monthly basis starting in 2010, and quarterly prior to that year.[3] For each individual, we have information on gender, age, nationality, family situation, employment status, start and end of employment, the employer's location, industry, and public-private ownership. The earnings variable refers to *all* work-related payments made by the employer in a given period that are subject to Social Security contributions, including base pay and non-regular payments such as bonuses, allowances, overtime pay, commissions, or severance payments.[4]

Following the conventions of the GRID project (Guvenen et al., 2022), we transform our original dataset into an annual panel of individuals. To characterize the dynamics of earnings inequality and risk, we rely on annual labor income, calculated by summing all employment-related payments received by an individual in a given year and expressed in real terms using the 2018 Consumer Price Index. In this panel, we impose two eligibility conditions to create our analysis sample: (i) individuals must be between the ages of 25 and 55 between 2000 and 2020, and (ii) annual earnings must be above a minimum earnings threshold, $Y_{min,t}$, which is equivalent to working part-time for a quarter at the national minimum wage.[5] This cut-off is meant to exclude individuals with weak attachment to the labor force.

From the annual panel, we create three main samples for our analysis: cross-sectional (CS), longitudinal (LS), and heterogeneity (H). The *CS*-sample refers to all observations included in the annual panel that satisfy the eligibility conditions on age

[2]The sampling procedure used by the Social Security Administration was based on year and month of birth, i.e., all individuals born in an odd month of each even year who had at least one day of contact with Social Security are included. This sampling design ensures that the sample is representative of the stock and flow of workers across all years, as shown in Figure A1 where we compare our data to the dynamics of wage employment and total compensation in the national accounts.

[3]Due to legal reasons, individuals do not appear in our sample until they are 18, even if they were present in the Social Security system at younger ages.

[4]Given the change in Social Security contributions in 2019, we recalculate earnings before the 2019 reform by multiplying them by the official re-scaling factor of 1.289.

[5]For example, the nominal value of the minimum threshold was equal to 240 Euros in 2000, 447 Euros in 2010, and 910 Euros in 2020. In Figure A2 in Appendix A, we show the evolution of annual earnings, the minimum earnings threshold, and the share of observations we drop each year due to the minimum earnings requirement.

and minimum earnings. The *LS*-sample further restricts the set of individuals to those with non-missing earnings observations in $t+1$ and $t+5$ so that individual-level earnings changes can be computed. The *H*-sample reduces the previous sample to those individuals who also have non-missing average earnings between t and $t-2$, so that measures of permanent earnings can be calculated.[6]

3 Two decades of labor earnings in Lithuania

In this section, we present a series of statistics on earnings dynamics in the Lithuanian Social Security data, separately for women and men. We first look at the evolution of inequality between 2000 and 2020. We then characterize the distributional properties of earnings growth by documenting higher-order moments of 1-year earnings changes. Finally, we examine income mobility over the life cycle and across the distribution. We do this by following the same individuals over time.

3.1 Labor earnings inequality

We begin our description of earnings dynamics in Lithuania by characterizing trends in inequality using the *CS*-sample, in which we retain all workers between the ages of 25 and 55 each year who meet the minimum earnings condition.[7]

Evolution of earnings percentiles. Figure 3 shows the development of the selected percentiles of log real earnings by gender, with 2000 as the reference year. Panels A and B display the 10th, 25th, median, 75th, and 90th percentiles separately for males and females. The figures illustrate that the significant wage increase documented in Section 2.1 extends to all parts of the distribution, with all the plotted percentiles roughly doubling with respect to their levels in 2000. The observed long-term growth was interrupted by the Great Recession when annual earnings fell substantially across the board, but this adjustment was somewhat larger for men. However, starting in 2012, all percentiles returned to the growth trend.

[6]Table A1 in the Appendix reports descriptive statistics for each of the samples in selected years.

[7]Figures A3 and A4 in the Appendix show all of the baseline results presented in this subsection using the pooled sample.

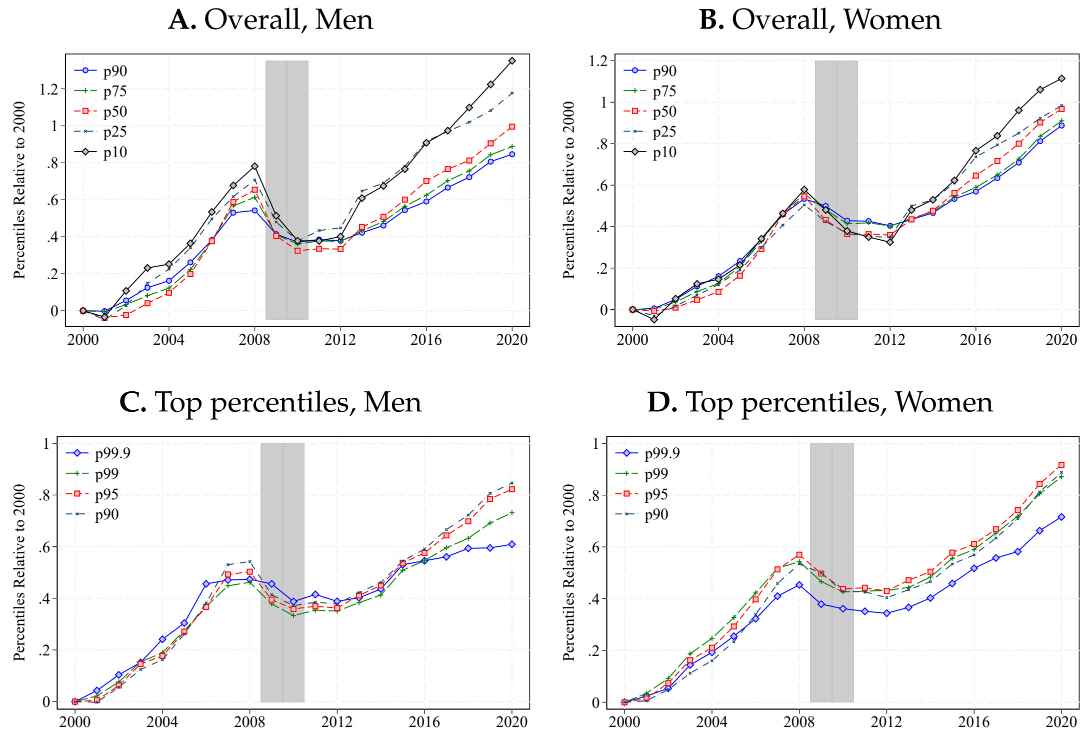


Figure 3: Percentiles of the distribution of log annual earnings by gender. *Note*: *CS*-sample. All percentiles are normalized to 0 in 2000. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

Although there has been substantial real earnings growth across all segments of the distribution, there are notable differences. Since the early 2000s, earnings at the bottom of the distribution have grown disproportionately more than those at the top.[8] For example, men's (women's) earnings at the 10th percentile have increased by about 130 (120) log points, while those at the 90th percentile have increased by 80 (90) log points. This heterogeneous pattern is particularly pronounced following the Great Recession when the most significant and sustained increases in the minimum wage took place (Garcia-Louzao and Tarasonis, 2023b).

Panels C and D of Figure 3 zoom in on the upper part of the earnings distribution. The dynamics of top percentiles show similar features: (i) a significant increase in their values, (ii) a strongly procyclical growth pattern, and, to a lesser extent, (iii) a negative relationship between the magnitude of earnings growth and the percentile level. Importantly, our data include only labor earnings and do not take into account capital or other sources of income, which may be more important for top earners and,

[8]In Figures A5 and A6 in the Appendix, we offer an alternative visualization comparing the income shares of each percentile.

therefore, may lead to different trends when analyzing broader income definitions.

Evolution of earnings inequality. In the top graphs of Figure 4, we plot the dynamics of overall inequality as measured by the P90-P10 percentile difference in log annual earnings or its standard deviation. As expected, given the trends of earnings percentiles discussed above, earnings inequality fell dramatically between 2000 and 2020 in Lithuania. Regardless of the measure, the evidence indicates that earnings inequality among men fell by roughly 20% (from 2.5 to 2), whereas the decline among women was about 11% (from 2.1 to 1.9).[9] The figure also depicts the cyclical component of earnings inequality, which jumped back to 2000 levels after the Great Recession but began a steeper decline afterward.[10]

In Panels C and D of Figure 4, our attention is directed towards the disparities at the upper and lower ends of the labor income spectrum, as measured by earnings percentiles differences, P90–P50 and P50–P10, respectively. For both genders, inequality fell on both sides of the earnings distribution. However, consistent with the faster growth of the lowest percentiles, the figure indicates a sharper decline in inequality at the bottom of the distribution, which became more pronounced in 2012. Thus, the contraction of the left tail of the distribution has played a critical role in the large decline in overall earnings inequality.

The large reduction in earnings dispersion is particularly noteworthy given that several countries experienced an increase in inequality over the same period (Guvenen et al., 2022). However, the patterns we uncover are similar to those of Brazil over a comparable period (Engbom et al., 2022) and Argentina's in the early 2000s (Blanco et al., 2022) from the GRID 1.0 countries and are shared by several Central and Eastern European economies, as documented by Magda et al. (2021) or Vacas-Soriano (2024) using different types of survey data.[11] Notably, despite a long-term decline, inequality

[9]In Figure A7 in the Appendix, we present Gini coefficients of annual earnings that convey the same message.

[10]The share of observations dropped due to the minimum earnings threshold being higher at the beginning of the period and during the Great Recession (see Figure A2 in the Appendix), which has potential implications for the inequality dynamics we uncover. More precisely, we may be underestimating the decline in inequality because the initial level of inequality would be higher if the minimum earnings threshold were not so binding in the early 2000s. By the same argument, we are likely to underestimate the increase in inequality during the economic downturn.

[11]Central and Eastern European economies tend to have large public sectors compared to more advanced economies. Given that public sector wage dynamics may differ from those in the private sector, in Appendix B, we replicate our main figures using only private sector workers (75% of the observations

in Lithuania is still high compared to other GRID 1.0 economies, significantly exceeding the levels observed in the Scandinavian countries and was lower only than Brazil, Argentina, Mexico, and the US.

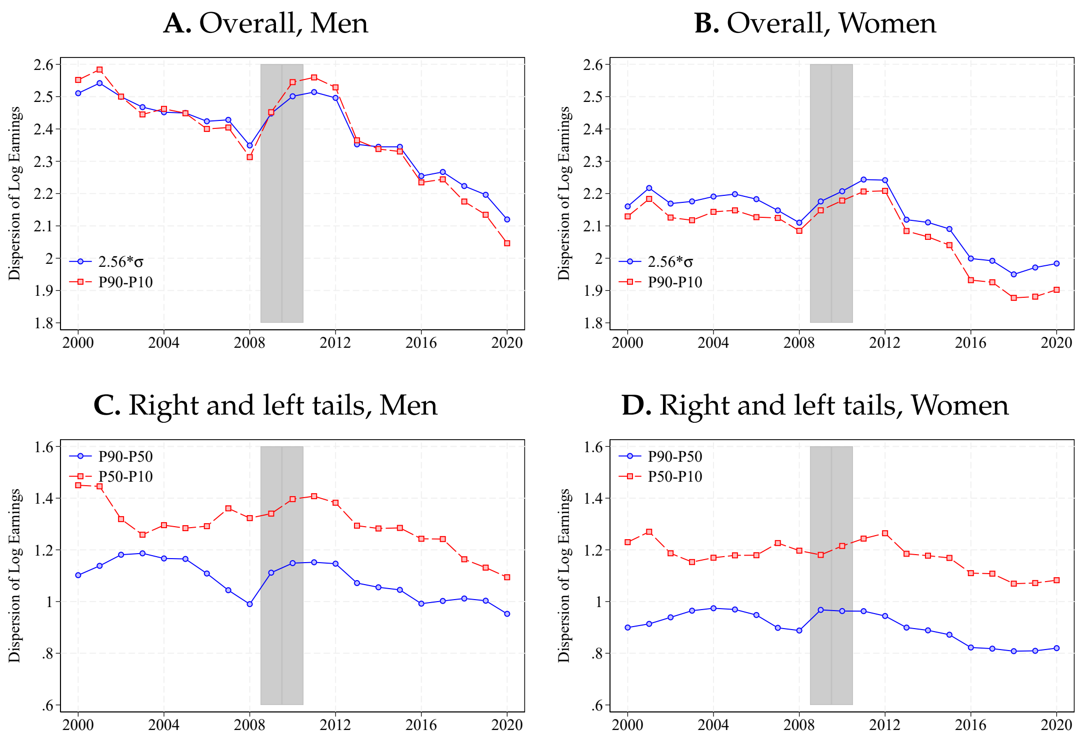


Figure 4: Earnings inequality, by gender. *Note*: *CS*-sample, σ denotes the standard deviation of log real annual earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

While the decline in inequality was evident in both halves of the distribution, the decline was more pronounced in the left tail, as income growth was particularly strong for the lowest percentiles. Several factors likely contributed to these dynamics. On the policy side, sustained increases in the minimum wage, which nearly quadrupled between 2000 and 2020, are likely to have played a role. Recent evidence from Černiauskas and Garcia-Louzao (2024) quantify that 32% of the decline in overall inequality and 40% of the decline in the bottom tail between 2010 and 2019 can be attributed to minimum wage policy. However, market forces may have been just as important. In particular, the mass emigration, especially of low-skilled workers, and the resulting tightening of the Lithuanian labor market following accession to the EU, which enabled free movement of workers from 2004, is likely to have contributed to

in our baseline sample). The results are quite similar in terms of trends in earnings inequality, although the statistics differ slightly in level.

the decline in inequality.[12] The existing evidence quantifies that a 1% increase in the emigration rate was associated with a 0.66% increase in the wages of those who stayed in Lithuania (Elsner, 2013). Complementing this explanation, Garcia-Louzao and Ruggieri (2023) examine changes in labor market competition and find that increases in competition might account for about 17% of the decline in wage inequality between 2000 and 2020.

Inequality of initial earnings and its dynamics. In Figure 5, Panels A and B show the evolution of *initial* inequality, defined as the dispersion of earnings among 25-year-olds.[13] We plot left and right tail inequality calculated as the difference between the median and the 10th percentile, P50-P10, and the 90th percentile and the median, P90-P50, respectively. Consistent with the aggregate trends, initial inequality is higher at the bottom of the distribution relative to the top, and both measures show more or less a declining trend. Thus, the decline in earnings inequality appears to be due not only to changes in earnings dynamics after labor market entry, but also to a decline in earnings among those entering the labor market. However, the figure reveals that initial inequality in the top half of the earnings distribution appears to have fallen more than overall inequality for the same segment of the distribution. The opposite is true regarding the bottom tail, especially among women. In addition, the earnings of new entrants at the lower end of the distribution do not appear to vary over the business cycle, while such patterns do emerge at the top. This pattern is similar for men and women. These findings may reflect different patterns of wage cyclicality across worker types, which translates into heterogeneous cyclical characteristics of earnings dispersion.

Panels C and D of Figure 5 offer a closer look at the impact of changes in initial conditions versus changes after entry into the labor market. Specifically, the connected lines show the age profile of earnings inequality of a given cohort, while the dashed lines characterize trends in the dispersion of earnings of different cohorts within a

[12]Figure A8 in the appendix shows the dynamics of the emigration rate between 2000 and 2020, along with the stock of emigrants by skill for selected years for which data are available. Given the size of the emigration flows, we have replicated our main inequality and earnings risk statistics for a selected sample of workers who do not have gaps in the annual panel and are, therefore, more likely to represent the population of stayers. The figures suggest that, despite differences in the levels of the statistics, the patterns we uncover remain unchanged, except for the dynamics of inequality around the Great Recession (see Appendix C).

[13]In Figure A9 in the Appendix, we also show the evolution of inequality at ages 35 and 45.

Figure 5: Inequality and age profiles for young workers, by gender. *Note*: *CS*-sample, Panels A and B consider only workers aged 25. Panels C and B plot earnings profiles by cohorts and age groups. *Source*: SoDra, 2000–2020.

given age group.[14] The figure shows that inequality, as measured by the P90-P10 log difference in annual earnings, decreased within age groups, in line with overall inequality trends. We also find that inequality is higher for older people, especially around the Great Recession. However, when we look at the evolution of selected cohorts as they age, a different pattern emerges: inequality declines over the life cycle. For women, the cohorts show qualitatively similar patterns, but the differences in initial levels of inequality are less pronounced. Moreover, the most recent cohort, women who turned 25 in 2016, shows an increasing trend in within-cohort inequality in the five years after entry despite lower initial levels of inequality. Strikingly, inequality across age groups was higher for younger women than older individuals before the Great Recession, but this shifted in the aftermath to follow the same pattern as men.

Taken together, our findings reveal a significant decline in income inequality among workers aged 25-55 in Lithuania, an almost unprecedented decline among GRID 1.0 countries. This decline is visible across genders and affects the upper and lower tails

[14] Recall that these profiles are based on the *CS*-sample, and thus individuals belonging to a particular cohort may not be observed in each of the years.

of the income distribution, suggesting that different economic mechanisms likely contribute to shaping inequality patterns (Ozkan et al., 2023).

3.2 Labor earnings risk

We now shift our focus to the properties of the income growth distribution to quantify the extent and magnitude of earnings shocks faced by Lithuanian workers. To this end, we compute 1-year-ahead residualized earnings changes using the *LS*-sample, i.e., individuals who meet the basic eligibility conditions as well as having valid observations in t and $t+1$.[15]

Evolution of dispersion in earnings risk. We start by looking at the dispersion of 1-year-ahead residualized earnings growth. This measure is typically interpreted as the degree of idiosyncratic labor earnings risk, and it is a critical determinant of inequality and consumption dynamics.

Panels A and B in Figure 6 illustrate the evolution of the standard deviation and P90-P10 differential in income growth distribution for both men and women. The standard deviation of 1-year-ahead log income changes is between 0.5 and 0.6, indicative of high earnings volatility. In other words, if the data were Gaussian, this would imply that the average worker in Lithuania experiences typical earnings shocks on the order of 50% to 60%. These figures reveal that Lithuania looks more similar to the United States (McKinney et al., 2022) and Brazil (Engbom et al., 2022), as earnings shocks are much larger than those in advanced European countries like Germany (Drechsel-Grau et al., 2022) or Sweden (Friedrich et al., 2022). Interestingly, despite the large decline in earnings inequality observed between 2000 and 2020, earnings risk has remained stable, with the only exception being the spike in risk during the Great Recession. This increase during the economic downturn is consistent with evidence from other countries, pointing to the countercyclical nature of earnings risk (Guvenen et al., 2022). The main difference emerges in terms of magnitude, where Lithuania stands out.

The figures also suggest that men faced slightly higher earnings risk than women at the beginning of the period and significantly higher earnings risk during the economic

[15] Figures A10, A11, and A12 in the Appendix replicate the analysis from this subsection, utilizing the change in earnings over a 5-year period instead of a 1-year period.

crisis, but the gap narrowed during the subsequent economic recovery. Importantly, this higher cross-sectional dispersion of male earnings growth is not present when considering only the private sector (see Appendix B), which is more consistent with the findings for GRID 1.0 countries. Thus, the lower earnings volatility for women may reflect a higher incidence of public sector jobs. Moreover, the gender gap is also reduced when looking at workers continuously registered with Social Security, suggesting that migration may contribute to this finding (see Appendix C).

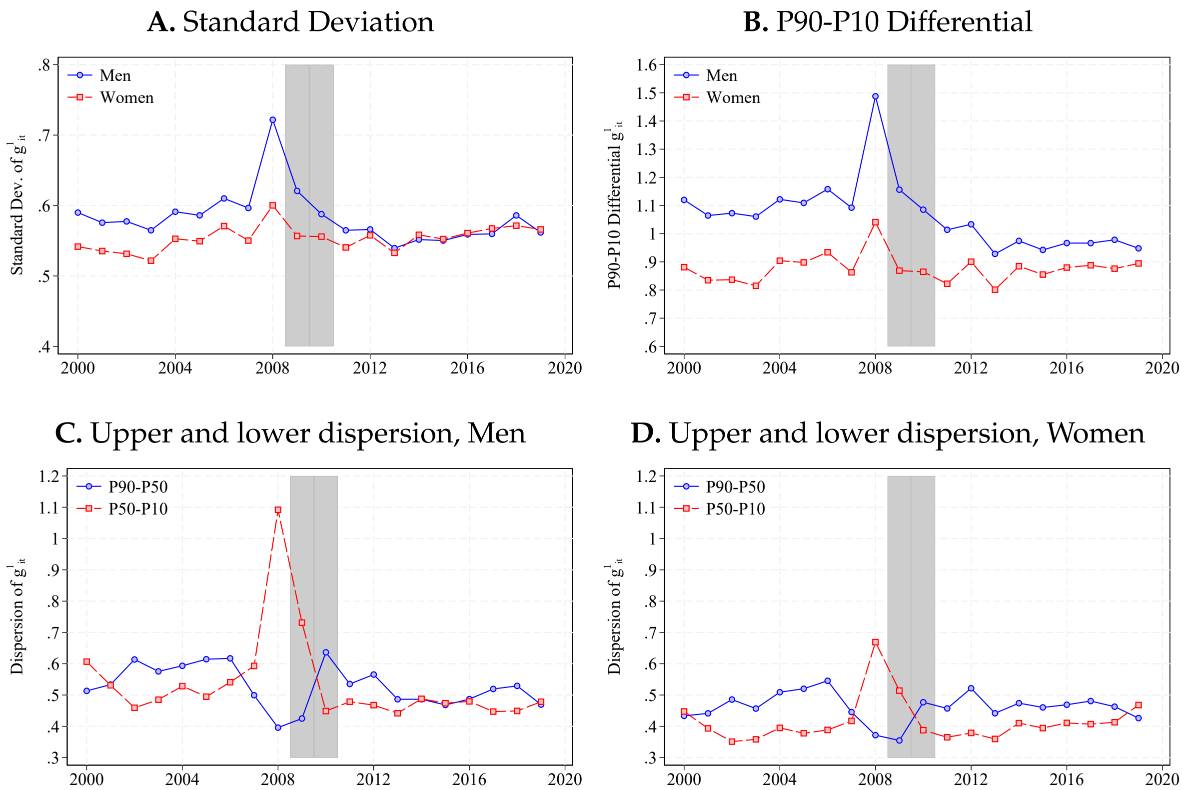


Figure 6: Dispersion of 1-year log earnings changes, by gender. *Note*: *LS*-sample, 1-year changes in residualized log earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

Panels C and D examine earnings changes' upper and lower dispersion, represented by the P90-P50 and P50-P10 percentile gaps, respectively. The figures reveal that the lower tail of earnings risk dispersion nearly doubled at the height of the financial crisis, reflecting larger downside risks. This sharp and abrupt increase in earnings risk likely stems from the severity of the economic shock experienced by Lithuania compared to other economies (Garcia-Louzao and Tarasonis, 2023a), coupled with significant nominal wage cuts implemented through internal devaluation as the primary mechanism for addressing the crisis (Masso and Krillo, 2011). In contrast, the upper tail dispersion of individual earnings growth declined substantially during this period, indicating a lower probability of upward surprises. This decline likely reflects widespread wage freezes, reduced upward job mobility, and associated returns during the recession (Carrillo-Tudela et al., 2022). These dynamics underscore the asymmetric nature of earnings risk during economic downturns, with workers more vulnerable to losses than gains, a pattern that holds for both genders.

Higher order moments of the dispersion in earnings risk. We now turn to characterize the degree of asymmetry (skewness) and the central tendency (kurtosis) of the dispersion of income growth. These measures are central to assessing potential deviations of the earnings process from log-normality, which is ultimately important for properly quantifying the welfare costs of earnings risk (Guvenen et al., 2024).

Panel A of Figure 7 shows the Kelley skewness of the distribution of 1-year-ahead earnings changes.[16] During economic expansions, the distribution is positively skewed as relatively large positive earnings shocks increase and relatively large negative earnings shocks decrease. The negative skewness of the earnings risk distribution emerges during the economic downturn, highlighting the impact of relatively large negative earnings shocks during this period and the limited incidence of positive earnings shocks. These cyclical dynamics are consistent with the uneven dynamics of the upper and lower tails of the distribution documented in Figure 6. The pronounced procyclicality of income change skewness has been documented in most countries from the first wave of the GRID. However, Lithuania's level of fall in skewness during the Great Recession is only comparable to Spain (Arellano et al., 2022). We quantify these procyclical fluctuations in Section 4.

Figure 7 Panel B plots the excess Crow–Siddiqui kurtosis of distribution of 1-year-ahead earnings changes.[17] The positive values observed in this measure indicate that the earnings risk distribution is leptokurtic: extreme events occur more frequently than predicted by a normal distribution. Put differently, in a given year, most indi-

[16] The Kelley skewness is defined as $K = \frac{(P90-P50)-(P50-P10)}{P90-P10}$. If the distribution is symmetric, $K = 0$. If there is more weight on the left (right) tail, the distribution is right-skewed (left-skewed), meaning the mean (median) exceeds the median (mean), $K > 0$ ($K < 0$).

[17] The excess Crow–Siddiqui kurtosis is defined as $CS = \frac{P97.5-P2.5}{P75-P25} - 2.91$ where the first term is the Crow-Siddiqi measure of kurtosis, and the 2.91 corresponds to the value of this measure for normal distribution. Values above zero imply that the distribution has a stronger central tendency than a normal distribution's benchmark.

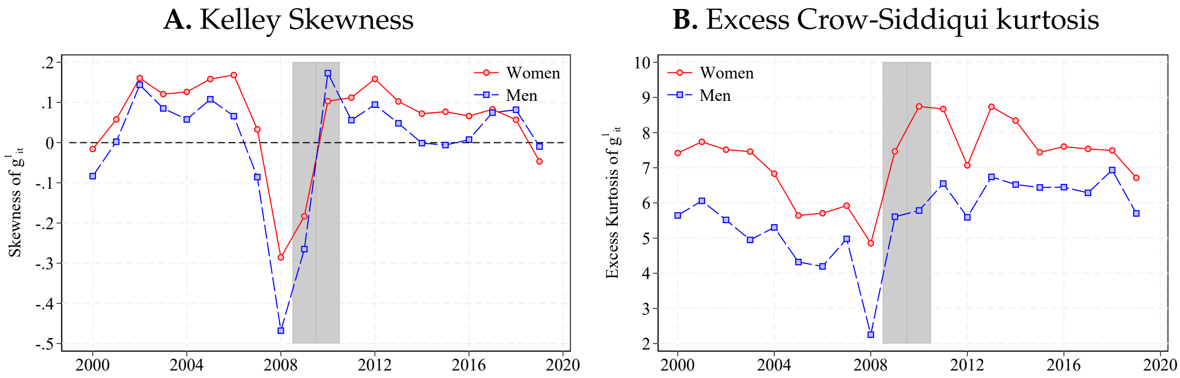


Figure 7: Kelly skewness and excess Crow–Siddiqui kurtosis of 1-year log earnings changes, by gender. *Note*: *LS*-sample, 1-year changes in residualized log earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

viduals experience very small earnings changes, while some workers experience very large changes in their earnings, resulting in a high kurtosis. Unlike the skewness of the earnings growth distribution, there is also a significant gender gap in the centrality of the earnings distribution. In other words, women are significantly more likely than men to experience very large changes in earnings, which may be partly explained by the generous length of maternity leave policies compared to other European economies (Bičáková and Kalíšková, 2022; Černiauskas, 2023). The gender gap in kurtosis of earnings growth rates is also present in Denmark (Leth-Petersen and Sæverud, 2022), Mexico (Puggioni et al., 2022), Sweden (Friedrich et al., 2022), and the United Kingdom (Bell et al., 2022).

In addition, consistent with most of the countries in the first wave of the GRID project, we document a procyclical behavior of excess kurtosis. Notably, the degree of excess kurtosis appears to have drifted upward somewhat in the aftermath of the economic downturn relative to the average pre-crisis value. Overall, due to non-zero skewness and a pronounced probability of extreme values, residual earnings changes deviate significantly from a normal distribution.[18]

Heterogeneity of earnings risk. To shed light on how earnings risk compares across age groups as well as along the distribution of permanent income, we leverage the *H*-

[18]Figures A13 and A15 in the Appendix graphically display the densities and the log-densities, respectively, of 1-year earnings changes against the densities of a normal distribution with similar variance to our data for 2005. Additionally, Figures A14 and A16 portray the same graphs but for 5-year earnings changes.

sample, where workers are further restricted to have at least two observations between t and $t-2$, and we define permanent income as the 3-year average of earnings in periods $t-2$, $t-1$, and t.

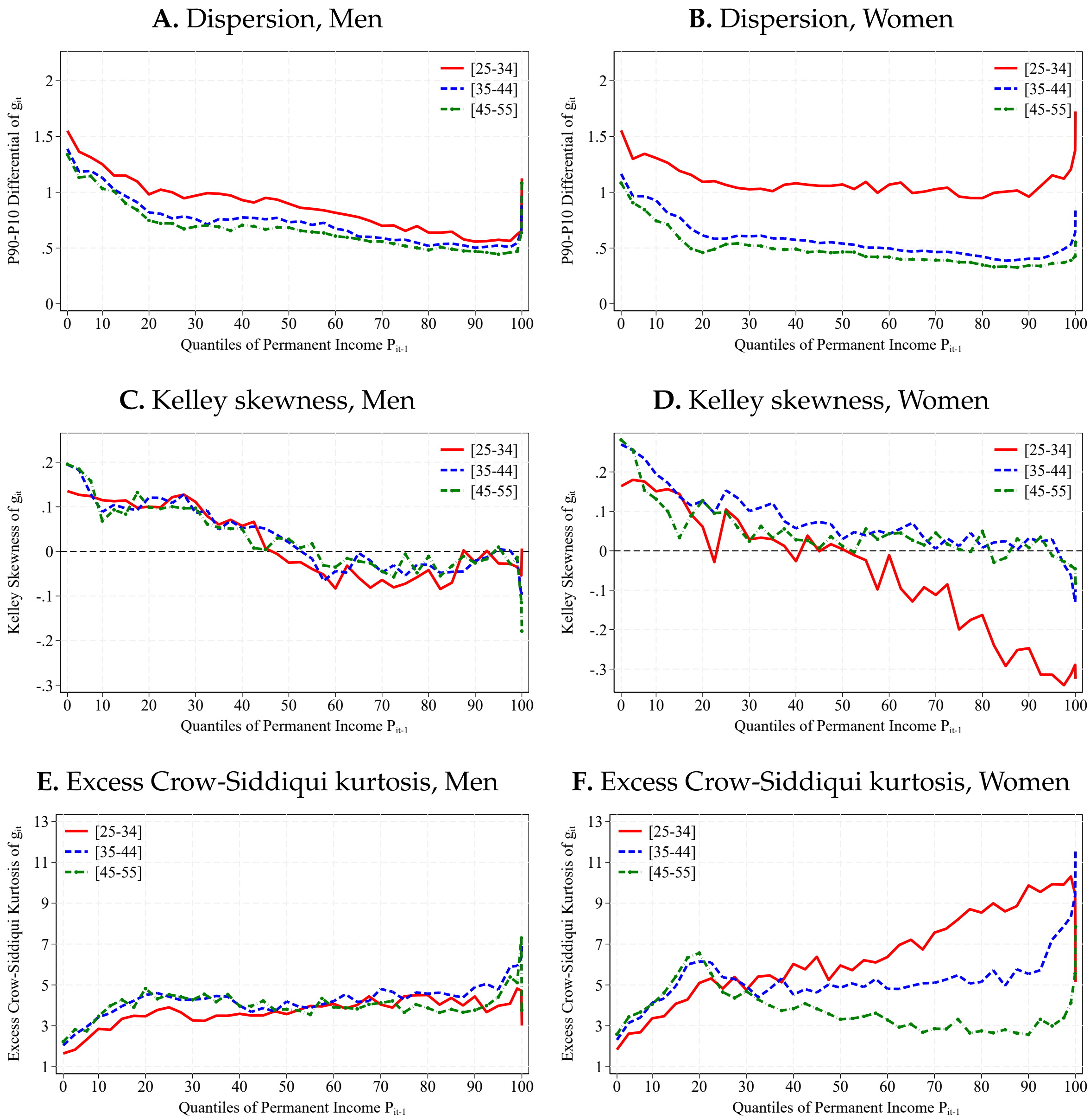


Figure 8: Dispersion, Skewness, and Kurtosis of 1-year log earnings changes by gender, age, and permanent income quantiles. *Note*: *H*-sample, 1-year changes in residualized log earnings. *Source*: SoDra, 2000–2020.

Panels A and B of Figure 8 show that the P90-P10 differential in earnings changes decreases steadily up to workers at the 90th percentile of the permanent income distribution and then increases again, especially at the top of the distribution. This pattern is more pronounced for men; for women, the earnings risk decreases sharply at the bottom of the permanent income distribution but varies little between the 20th and 90th percentiles. The volatility of earnings changes also appears to be somewhat higher for men than for women aged 35 to 55, but younger women have higher levels of earnings risk across the distribution. The age profile and the decreasing pattern of the dispersion of 1-year-ahead earnings changes along the permanent income distribution are common to most countries in the GRID project. Notably, while the significantly higher earnings risk of women aged 25-34 across the distribution is a feature of several GRID countries, the profile of Lithuanian young women is mainly comparable to that of Sweden (Friedrich et al., 2022) where differences in earnings across the permanent income distribution for young women are mild. However, young women at the top of the distribution show comparable levels of earnings risk to those at the bottom, similar to German young women (Drechsel-Grau et al., 2022).

Looking at the symmetry of the distribution of 1-year-ahead (log) earnings changes, Panels C and D of Figure 8 illustrate that the skewness of the distribution for men tends to be positive for individuals up to the median of the permanent income distribution and close to zero for those above it. The figure shows a similar pattern for women aged 35 to 55. However, young women whose permanent income is above the median have earnings changes that are negatively skewed. These negative skewness values for young women in the upper half of the distribution suggest that the higher volatility of earnings changes documented above is largely due to these women experiencing a disproportionate incidence of earnings losses, a feature common to most GRID countries.[19] The higher incidence of negative earnings shocks for this group of women can be explained by employment interruptions due to childbearing. Interestingly, when looking at earnings changes 5 years ahead, the skewness of the distribution becomes negative for all individuals, regardless of gender or age, in the upper half of the distribution, but the magnitudes hardly change for young women (see Figure A12 in Appendix A), supporting the idea that negative earnings shifts for these women are associated with having children.

Panels E and F of Figure 8 show the excess Crow–Siddiqui kurtosis of the distribution of 1-year-ahead (log) earnings changes, indicating that the distribution of idiosyncratic earnings risk for both men and women has a stronger central tendency than

[19]Only Mexico (Puggioni et al., 2022) and Brazil (Engbom et al., 2022) exhibit non-negative values of skewness for young women.

the normal distribution would imply. Focusing on men, the excess kurtosis increases steadily up to the 20th percentile of the permanent income distribution, somewhat faster for older individuals. Interestingly, the values stabilize between the 20th and 90th percentiles, and there are roughly no differences across age groups in the top half of the permanent income distribution. At the very top, the excess kurtosis increases again, more so for men aged 35 to 55. While several countries share the increasing pattern at the bottom of the distribution, the profile of excess kurtosis higher up in the permanent income distribution seems unique to Lithuania compared to the countries in the first wave of GRID.

With respect to women, the dynamics in the bottom part of the distribution are similar to that of men, but the increases are of greater magnitude. Interestingly, the age differences are quite pronounced for women whose permanent income is above the 30th percentile, with the three age groups showing different patterns. For the older group, women aged 45 to 55, excess kurtosis decreases up to the 90th percentile and then increases sharply. For women between the ages of 35 and 44, the excess kurtosis remains roughly constant around a value of 5 until the 90th percentile, where it rises steadily. Finally, for young women, the values gradually increase across the permanent income distribution, suggesting that tail events are increasing in permanent income for this group, only to drop suddenly for women above the 95th percentile. This different pattern in excess kurtosis across the age and permanent income distribution for women is only comparable to the findings for Italy (Hoffmann et al., 2022) and to a lesser extent for Germany (Drechsel-Grau et al., 2022), but the dynamics at the top of the distribution, again, seem to be particular to the Lithuanian case.

In summary, we document non-Gaussian properties of income growth in line with the recent empirical findings in other countries (Busch and Ludwig, 2024). However, we also show that income volatility in Lithuania is relatively high compared to GRID 1.0 countries, especially European economies, and has changed little over time. Finally, we uncover significant heterogeneity in income dynamics, with low-income groups and young workers (especially women) experiencing higher levels of risk.

3.3 Labor earnings mobility

How individuals move across the income distribution is a critical aspect of inequality. In this section, we characterize earnings mobility for men and women by looking at different age groups and points in time.

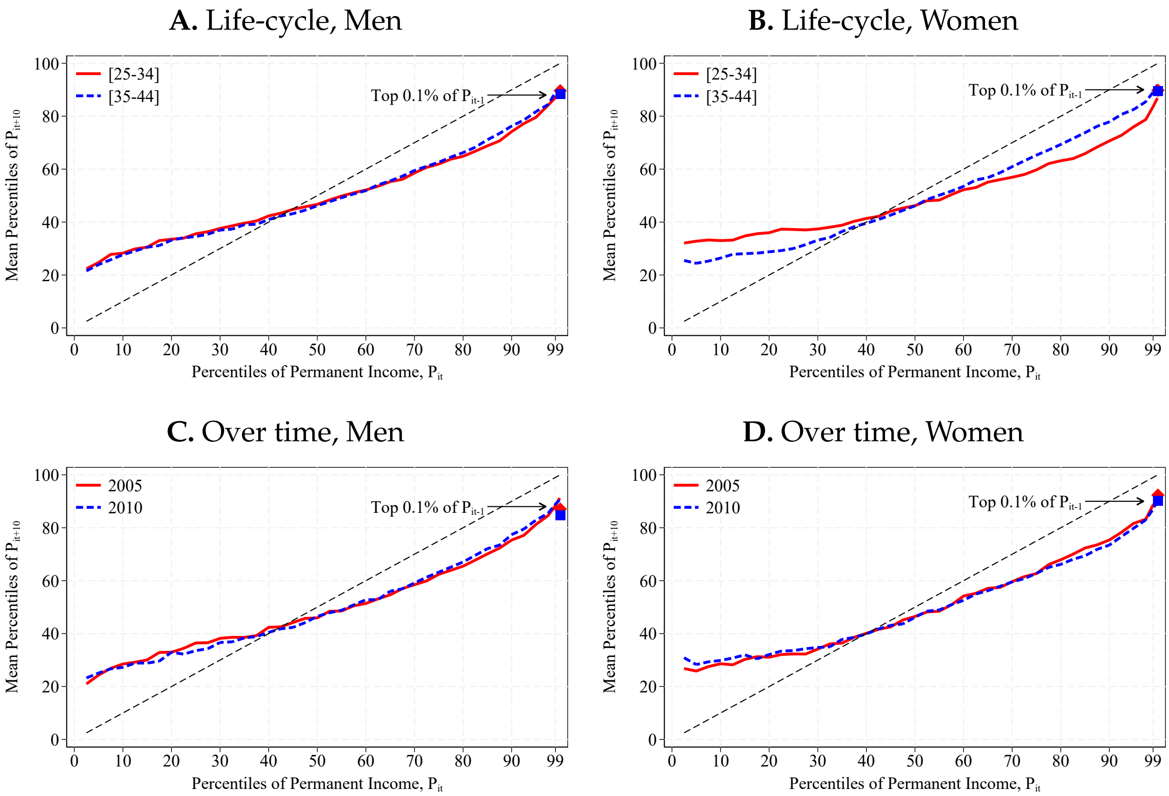


Figure 9: Evolution of 10-year income mobility. *Note*: *H*-sample, average rank-rank mobility for men and women. Panels A and B look at different age groups, while panels C and D compare mobility using two alternative base years, 2005 and 2010, and averaging across all age groups. The black diagonal dashed line is the 45-degree line that corresponds to the case of no mobility. *Source*: SoDra, 2000–2020.

Figure 9 presents 10-year mobility statistics.[20] In Panel A and B, we rank each individual i based on their permanent income in period t. For each percentile of the permanent earnings distribution at time t, we then calculate the average rank of all individuals in that percentile 10 years later. We then plot this measure over a 10-year period by sex and age. The figures reveal significant upward rank mobility below the 40th percentile and downward mobility above it in the permanent earnings distribution for men. For example, male workers at the 10th percentile of the permanent

[20]Mobility patterns are very similar when looking at shorter horizons; see Figures A17 and A18 in the Appendix.

income distribution manage, on average, to move up the distribution to be between the 25th and 30th percentiles after 10 years. Moreover, mobility among young men appears to be only slightly higher than among older men. The picture is different for women, as young women experience significantly higher mobility, both upward and downward, than men and older women. For example, on average, young women at the bottom of the permanent earnings distribution move to the 30th percentile after 10 years. However, those at the 90th percentile fall to around the 70th percentile on average over 10 years. Interestingly, income mobility appears to be fairly stable over our sample period, as suggested by Panels C and D.[21]

To put our results into perspective with respect to the first wave of GRID, we follow Guvenen et al. (2022) and provide key statistics on 5-year rank persistence over the life cycle. Table A2 of the Appendix shows that the rank-rank slope in Lithuania is 0.68, which is significantly lower than in most countries from the first wave of GRID and comparable only to the Nordic countries (Denmark, Norway, and Sweden), which are known for their high levels of intragenerational mobility. The expected rank five years ahead for individuals below and above the median is 33.1 and 66.9, respectively, indicating that both downward and upward mobility contribute to the overall lack of rank persistence.

To summarize, we replicate the augmented Great Gatsby curve from Guvenen et al. (2022), which correlates inequality, as measured by the Gini coefficient, with the estimates of income rank persistence over 5 years, and include two data points for Lithuania – the first and the last within our time window.[22] Figure 10 reveals that the Lithuanian economy deviates from the curve, as it features high income inequality and low persistence in permanent income ranks (high mobility). Interestingly, given the mobility rates, the large decline in income inequality over the last two decades has moved Lithuania closer to the Nordic countries.

[21] In Appendix Figures A17 and A18, we show additional results on 5-year mobility over the life cycle and over time.

[22] The Great Gatsby curve denotes the positive relationship between cross-sectional income inequality and the persistence of intergenerational mobility (Durlauf and Seshadri, 2018). However, this relationship also extends to intragenerational mobility, as shown by Guvenen et al. (2022).

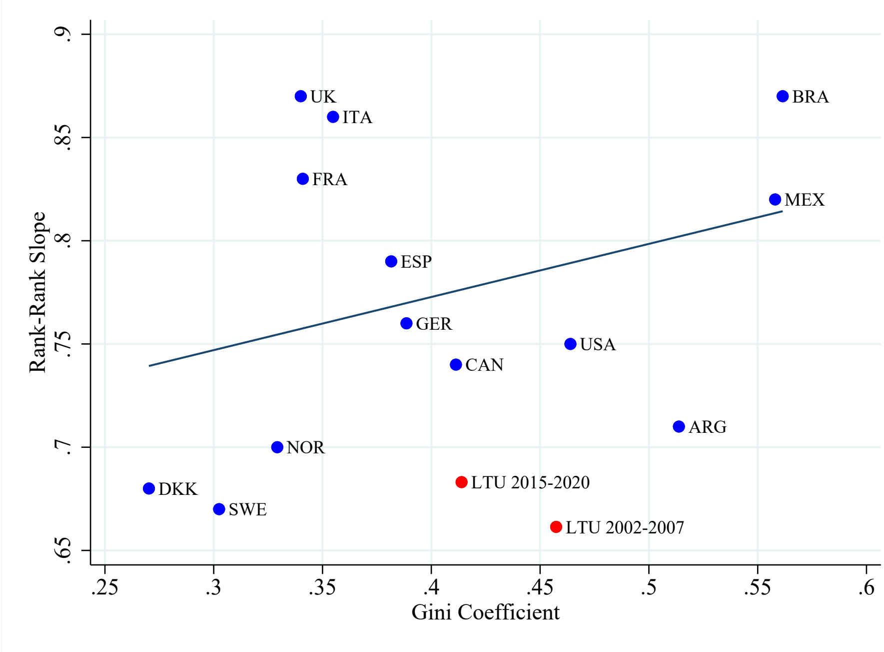


Figure 10: Great Gatsby curve. *Note*: Gini Coefficient and Rank-Rank slopes are averaged over two distinct periods for Lithuania (2002–2007 and 2015–2020), while for all other countries, the averages are calculated over the period 1997–2007. *Source*: SoDra, 2002-2020 for Lithuania, the first wave of GRID for all other countries (Guvenen et al., 2022).

4 Economic growth and labor earnings dynamics

Having presented a set of stylized facts about labor earnings across cross-sections and over time, we now examine how earnings dynamics are related to macroeconomic developments in the Lithuanian economy between 2000 and 2020. We also examine its heterogeneity to round out the evidence on the dynamics of inequality and the heterogeneity of earnings risk along the permanent income distribution. For this purpose, we focus on the H-sample and look at 1-year (log) earnings changes.

GDP betas. We relate individual earnings changes to GDP growth following Guvenen et al. (2017). In particular, we estimate a series of linear regressions of the form

$$\Delta y_{it} = \alpha_g + \beta_g \Delta Y_t + \epsilon_{it} \tag{1}$$

where y_{it} denotes the (log) real annual earnings of individual i in year t and Y_t is the (log) real GDP in year t. Δ represents changes between t and $t+1$ in both y_{it} and Y_t. We estimate Equation (1) separately by groups, g, defined by sex, three age categories, and 20 percentiles of the permanent labor earnings distribution. Using the labeling of Guvenen et al. (2017), β_g is the GDP beta of workers in group g, which refers to the aggregate risk of individual earnings growth in that category.

In addition, we take the 1-year-ahead individual earnings growth and compute the 2nd, 3rd, and 4th moments of its distribution. We then follow Busch et al. (2022) to correlate these distributional moments with the GDP growth

$$m(\Delta y_{it}) = \gamma_g + \phi_g^m \Delta Y_t + \lambda_g t + \varepsilon_{it} \tag{2}$$

where $m(\cdot)$ is the specific moment, i.e., P90-P10 differential, skewness, or excess kurtosis, of the distribution of 1-year-ahead individual earnings growth, Δy_{it}, that we compute separately for the same g-groups defined above. ΔY_t refers to the 1-year-ahead GDP growth and t represents a linear time trend.

Labor earnings growth and the macroeconomy. In Table 1 we start with the average GDP beta estimates for different moments of the distribution, separately for men and women. Column (1) shows the elasticity of individual earnings growth with respect to GDP growth: a contemporaneous 1% increase in real GDP is correlated with an average growth in real annual earnings of 1.3% for men, while the figure is 0.7% for women. These estimates suggest a higher sensitivity of earnings to business cycle fluctuations than in the literature, consistent with the procyclical behavior of the labor share shown in Panel C of Figure 2 and evidence pointing to a higher degree of wage cyclicality in Eastern Europe (Nickel et al., 2019; Garcia-Louzao and Jouvanceau, 2023).[23] The lower sensitivity for women relative to men is in line with the findings for the US (Guvenen et al., 2017) or the results in Bell et al. (2022) for the UK within the GRID project.

Column (2) reveals that as GDP increases, the dispersion of (log) earnings changes decreases for men, but there is no statistically significant association for women. This is consistent with the impression in Figure 6, which suggests a less volatile pattern in earnings growth dispersion for women. The strong countercyclical correlation between the dispersion of earnings changes and the business cycle for men contrasts

[23] A common explanation for the high responsiveness of wages to business cycle fluctuations in Central and Eastern Europe is the low coverage of collective bargaining, which allows firms to change wages more frequently (Druant et al., 2012).

Table 1: GDP betas of idiosyncratic earnings risk

	(1) Growth	(2) P90-P10	(3) Kelley	(4) Kurtosis
A. Men				
GDP beta	1.300***	-1.046***	1.816***	9.895***
	(0.006)	(0.147)	(0.120)	(2.299)
B. Women				
GDP beta	0.669***	-0.135	0.997***	5.613***
	(0.004)	(0.106)	(0.076)	(1.398)

Note: H-sample, 1-year changes in log earnings. Column (1) reports the β estimate of Equation (1), while Columns (2) to (4) report the moment-specific ϕ^m estimate of Equation (2). The g-groups are defined by sex only. Robust standard errors are in parentheses. *Source*: SoDra, 2000–2020

with the weaker relationship in Denmark reported in Leth-Petersen and Sæverud (2022) or for the US, Sweden, and Germany analyzed by Busch et al. (2022), whose results are mostly comparable to our findings for women.

The sex differences in GDP betas also hold for the 3rd (Kelley skewness) and 4th (excess kurtosis) moments of the distribution of 1-year (log) earnings changes, as reported in Columns (3) and (4), respectively. In particular, our elasticities imply a higher sensitivity to the business cycle for men than women compared to previous studies (Busch et al., 2022; Leth-Petersen and Sæverud, 2022). However, our estimate ϕ^{Kelley} is at the lower bound of existing estimates and is more comparable to the US than to other European economies documented by Busch et al. (2022). With respect to the sensitivity of kurtosis to GDP growth, we find a significant correlation between excess kurtosis and GDP growth while Leth-Petersen and Sæverud (2022) find very imprecise estimates for Denmark. Yet, the magnitude of our estimates for men is comparable to those of Leth-Petersen and Saeverud (they found 11.2 in Denmark), although we find a 5 times lower sensitivity for women.

Heterogeneous GDP betas. We now turn to characterize whether the sensitivity of earnings dynamics to GDP growth varies across the permanent income distribution. In other words, we are interested in understanding whether some workers are more exposed to aggregate dynamics than others.

Figure 11 reports the β_g-estimates from Equation (1), with Panel A focusing on men and Panel B on women. Regardless of the quantile of permanent income, the results suggest that men's earnings risk is more sensitive to business cycle fluctuations than women's. To put the magnitude in context, Guvenen et al. (2017) estimate a GDP beta for the median US worker aged 35-44 of 1.09 for men and 0.69 for women; the figures for Lithuania are 1.40 and 0.75 for men and women, respectively. While we find, in line with the previous literature, that individuals at the bottom of the permanent income distribution are most affected by aggregate fluctuations, our estimates suggest only a decreasing pattern, in contrast to the US, where GDP betas are U-shaped with respect to permanent income levels.[24] Our results are, instead, more similar to those for the UK (Bell et al., 2022) or Germany (Broer et al., 2020).[25] Finally, GDP betas do not seem to show substantial differences across age for women, and only young men (25-34) at the bottom of the distribution show higher sensitivity of earnings growth to the business cycle relative to older men.

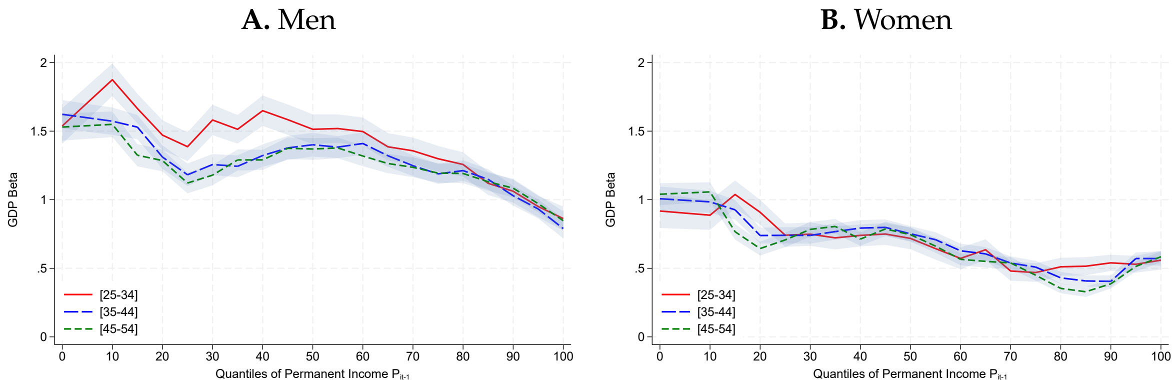


Figure 11: Heterogeneous GDP betas. *Note*: H-sample, 1-year changes in log earnings. β_g estimates of Equation (1). Shaded areas represent 95% confidence intervals based on robust standard errors. *Source*: SoDra, 2000–2020.

Figure 12 plots GDP betas for higher order moments of the distribution of 1-year (log) earnings changes along the permanent income distribution by age group and sex. Panels A and B reveal that GDP growth does not translate into a reduction in the P90-P10 differential for all individuals along the income distribution. For men below the 20th percentile of the permanent income distribution, we find no correlation between aggregate dynamics and the dispersion of individual (log) earnings changes. Instead,

[24]Appendix C in Amberg et al. (2022) also documents a U-shaped pattern of individual earnings growth to aggregate risk in Sweden.

[25]Broer et al. (2020) shows that the U-shaped pattern emerges when focusing on individuals employed in t and $t+h$, suggesting an important role in labor market transitions.

the uncovered correlation between earnings growth dispersion and GDP growth in Table 1 is driven by individuals above the 30th percentile. The picture is interestingly different for women, as there is noticeable age heterogeneity. More specifically, for women aged 24-34, we document a small but positive correlation between GDP growth and the dispersion of individual earnings changes, suggesting that dispersion among these individuals increases as GDP expands. In contrast, we find a somewhat U-shaped pattern for older women, with no correlation between dispersion and GDP growth for individuals below the 20th percentile, a sharp decline between the 20th and 30th percentiles, and a slight increase to remain small and negative. The overall patterns are similar to those reported by Leth-Petersen and Sæverud (2022) for Denmark, with some size differences in the magnitude of the GDP betas.

Panels C and D of Figure 12 plot the GDP betas for the 3rd moment (skewness) of the distribution of 1-year (log) earnings changes. For men, the estimates suggest a hump-shaped pattern in the sensitivity of skewness to GDP growth, with the estimated coefficient increasing up to the 30th percentile for those aged 25-34 (40th percentile for those aged 35-55) and then declining slowly but remaining stable from the median of the permanent income distribution onwards. This shape of GDP betas of skewness along the distribution is similar to Denmark (Leth-Petersen and Sæverud, 2022), but in comparison to our results, the peak occurs earlier in the distribution for older males. In addition, the magnitude is larger, implying a steeper decline from the peak. For women, our estimates suggest a similar hump-shaped pattern as for men, but the magnitude of the GDP betas is smaller, as already suggested by the results in Table 1. Interestingly, the age heterogeneity is also more pronounced for women, with young women having significantly lower GDP betas, even below zero. Comparing our estimates with those of Denmark, the magnitude of the GDP betas is similar, as are the lower (even negative) estimates for younger women.

Finally, we examine the evolution of excess kurtosis as GDP grows in Panels E and F of Figure 12. The estimates reveal that for workers at the bottom of the permanent income distribution, the sensitivity of excess kurtosis to GDP growth is roughly zero for both men and women. The magnitude of the estimate jumps to around 10 and remains stable from the 20th percentile onward in the case of men, with little age heterogeneity. For women aged 35-55, the level of sensitivity of excess kurtosis also drifts

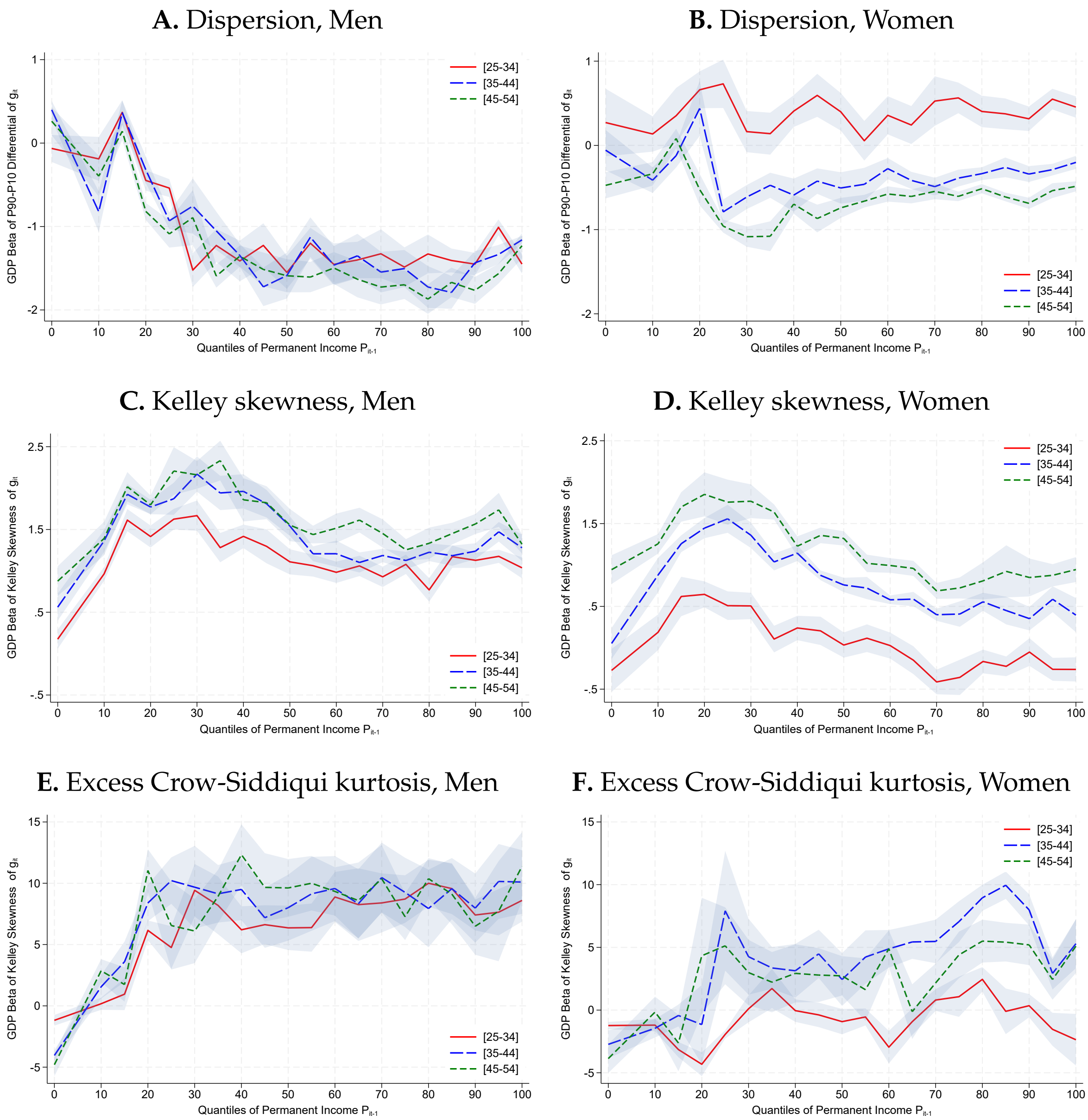


Figure 12: Heterogeneous GDP betas of Dispersion, Skewness, and Kurtosis. *Note*: *H*-sample, 1-year changes in log earnings. ϕ_g estimates of Equation (1). Shaded areas represent 68% confidence intervals based on robust standard errors. *Source*: SoDra, 2000–2020.

up from the 20th percentile and remains stable up to the median of the distribution, and then continues to increase for the middle age cohort (aged 35-44). The exception is again the younger cohort of women. They have GDP betas with excess kurtosis that are close to zero along the permanent income distribution. The degree and heterogeneity of the sensitivity of the excess kurtosis to GDP growth contrasts with the estimates for Denmark, where these GDP betas are flat around zero for both men and women as well as across age groups (Leth-Petersen and Sæverud, 2022).

Overall, our estimates show a relatively high sensitivity of earnings growth to GDP growth in Lithuania compared to other economies, more so for men and low-income workers. Moreover, we document substantial heterogeneity in the correlation between earnings risk and GDP growth: risk for low-income workers does not vary with GDP, while for individuals higher in the distribution, the risk decreases, and the probability of large positive earnings shocks increases with economic growth. These patterns are less pronounced for women.

5 Conclusions

This paper uses Social Security data to provide new stylized evidence on earnings inequality, risk, and mobility in Lithuania between 2000 and 2020. During this period, the Lithuanian economy experienced sustained economic growth, which contributed to earnings growth across the income distribution. However, earnings growth was more pronounced in the lower tail, leading to a significant decline in earnings inequality. Importantly, when we relate changes in individual earnings to GDP growth, Lithuania shows a higher sensitivity than other countries, especially for low-income workers. This higher sensitivity partly explains the overall decline in inequality, but also the sharp increase during the Great Recession. In addition to economic growth, the continuous increases in the minimum wage and labor market tightening have also played a role. Notably, despite the substantial decline in earnings inequality, it remains high relative to most advanced European economies.

The relatively high remaining level of inequality is likely to be related to earnings risk, which is not evenly distributed across the population. Our analysis shows that the dispersion of earnings changes (risk) has remained relatively stable, but is higher for low-income workers. Importantly, we find that earnings risk remains constant as GDP grows for low-income workers, while it declines as one moves up the permanent income distribution. This suggests that while economic development may have benefited the earnings growth of low-income workers, it has not reduced their exposure to (sizable) earnings volatility. Moreover, our characterization of the earnings growth distribution reveals substantial deviations from the log-normality assumption of income processes and these patterns are heterogeneous over time and across workers.

The presence of such deviations implies that the welfare costs of income risk may exceed the estimates provided by conventional approaches (Guvenen et al., 2024).

Taken together, our results suggest that a better understanding of the underlying sources of earnings risk is essential to formulate policies that effectively reduce the level of risk faced by low-income workers and, ultimately, help to address the remaining high levels of labor market inequality.

References

Amberg, N., Jansson, T., Klein, M., and Picco, A. R. (2022). Five facts about the distributional income effects of monetary policy shocks. *American Economic Review: Insights*, 4(3):289–304.

Arellano, M., Bonhomme, S., De Vera, M., Hospido, L., and Wei, S. (2022). Income risk inequality: Evidence from spanish administrative records. *Quantitative Economics*, 13(4):1747–1801.

Banks, J., Blundell, R., Bozio, A., Cribb, J., Green, D., and Ziliak, J. P. (2024). Changing labour market and income inequalities in europe and north america: a parallel project to the ifs deaton review of inequalities in the 21st century. *Fiscal Studies*, 45(2):111–117.

Bell, B., Bloom, N., and Blundell, J. (2022). Income dynamics in the United Kingdom and the impact of the Covid-19 recession. *Quantitative Economics*, 13(4):1849–1878.

Bičáková, A. and Kalíšková, K. (2022). Career-breaks and maternal employment in CEE countries. In Molina, J. A., editor, *Mothers in the Labor Market*, pages 159–215. Springer International Publishing, Cham.

Blanco, A., Diaz de Astarloa, B., Drenik, A., Moser, C., and Trupkin, D. R. (2022). The evolution of the earnings distribution in a volatile economy: Evidence from Argentina. *Quantitative Economics*, 13(4):1361–1403.

Broer, T., Kramer, J., and Mitman, K. (2020). The curious incidence of shocks along the income distribution. *mimeo*.

Busch, C., Domeij, D., Guvenen, F., and Madera, R. (2022). Skewed idiosyncratic income risk over the business cycle: Sources and insurance. *American Economic Journal: Macroeconomics*, 14(2):207–242.

Busch, C. and Ludwig, A. (2024). Higher-order income risk over the business cycle. *International Economic Review*, 65(3):1105–1131.

Carrillo-Tudela, C., Visschers, L., and Wiczer, D. (2022). Cyclical earnings, career and employment transitions. *CESifo Working Paper No. 9990*.

Černiauskas, N. (2023). The short run effects of childbirth on parents' earnings in the Baltics. *Baltic Journal of Economics*, 23(1):45–63.

Černiauskas, N. and Garcia-Louzao, J. (2024). The earnings distribution in Lithuania: The role of the minimum wage. *Bank of Lithuania Discussion Papers No. 37*.

Černiauskas, N., Sologon, D. M., O'Donoghue, C., and Tarasonis, L. (2022). Income inequality and redistribution in lithuania: The role of policy, labor market, income, and demographics. *Review of Income and Wealth*, 68:S131–S166.

Ding, Z., Garcia-Louzao, J., and Jouvanceau, V. (2025). The dynamics of product and labor market power: Evidence from Lithuania. *Ecnomics of Transition and Institutional Change*, 33(1):165–194.

Drechsel-Grau, M., Peichl, A., Schmid, K. D., Schmieder, J. F., Walz, H., and Wolter, S. (2022). Inequality and income dynamics in Germany. *Quantitative Economics*, 13(4):1593–1635.

Druant, M., Fabiani, S., Kezdi, G., Lamo, A., Martins, F., and Sabbatini, R. (2012). Firms' price and wage adjustment in europe: Survey evidence on nominal stickiness. *Labour Economics*, 19(5):772–782.

Durlauf, S. N. and Seshadri, A. (2018). Understanding the Great Gatsby curve. *NBER Macroeconomics Annual*, 32(1):333–393.

Elsner, B. (2013). Does emigration benefit the stayers? Evidence from EU enlargement. *Journal of Population Economics*, 26:531–553.

Engbom, N., Gonzaga, G., Moser, C., and Olivieri, R. (2022). Earnings inequality and dynamics in the presence of informality: The case of Brazil. *Quantitative Economics*, 13(4):1405–1446.

Fic, T., Holland, D., Paluchowski, P., Rincon-Aznar, A., and Stokes, L. (2011). Labour mobility within the EU–The impact of enlargement and transitional arrangements. *National Institute of Economic and Social Research Discussion Paper No. 379*.

Friedrich, B., Laun, L., and Meghir, C. (2022). Earnings dynamics of immigrants and natives in Sweden 1985–2016. *Quantitative Economics*, 13(4):1803–1847.

Garcia-Louzao, J. and Jouvanceau, V. (2023). Wage growth in Lithuania from 2008 to 2020: Observed drivers and underlying shocks. *Baltic Journal of Economics*, 23(2):117–141.

Garcia-Louzao, J. and Ruggieri, A. (2023). Labor market competition and inequality. *CESifo Working Paper No. 10829*.

Garcia-Louzao, J. and Tarasonis, L. (2023a). Productivity-enhancing reallocation during the Great Recession: Evidence from Lithuania. *Oxford Economic Papers*, 75(3):729–749.

Garcia-Louzao, J. and Tarasonis, L. (2023b). Wage and employment impact of minimum wage: Evidence from Lithuania. *Journal of Comparative Economics*, 51(2):592–609.

Garcia-Louzao, J. and Vėlyvis, K. (2021). Beyond the traditional unemployment rate during Covid-19 in Lithuania. *Bank of Lithuania Ocassional Papers No. 40*.

Guvenen, F., Ozkan, S., and Madera, R. (2024). Consumption dynamics and welfare under non-gaussian earnings risk. *NBER Working Paper No. 32298*.

Guvenen, F., Ozkan, S., and Song, J. (2014). The nature of countercyclical income risk. *Journal of Political Economy*, 122(3):621–660.

Guvenen, F., Pistaferri, L., and Violante, G. L. (2022). Global trends in income inequality and income dynamics: New insights from GRID. *Quantitative Economics*, 13(4):1321–1360.

Guvenen, F., Schulhofer-Wohl, S., Song, J., and Yogo, M. (2017). Worker betas: Five facts about systematic earnings risk. *American Economic Review*, 107(5):398–403.

Hoffmann, E. B., Malacrino, D., and Pistaferri, L. (2022). Earnings dynamics and labor market reforms: The Italian case. *Quantitative Economics*, 13(4):1637–1667.

Klüsener, S., Stankūnienė, V., Grigoriev, P., and Jasilionis, D. (2015). The mass emigration context of Lithuania: Patterns and policy options. *International Migration*, 53(5):179–193.

Leth-Petersen, S. and Sæverud, J. (2022). Inequality and dynamics of earnings and disposable income in Denmark 1987–2016. *Quantitative Economics*, 13(4):1493–1526.

Magda, I., Gromadzki, J., and Moriconi, S. (2021). Firms and wage inequality in Central and Eastern Europe. *Journal of Comparative Economics*, 49(2):499–552.

Masso, J. and Krillo, K. (2011). Mixed adjustment forms and inequality effects in Estonia, Latvia and Lithuania. In *Work Inequalities in the Crisis*. Edward Elgar Publishing.

McKinney, K. L., Abowd, J. M., and Janicki, H. P. (2022). US long-term earnings outcomes by sex, race, ethnicity, and place of birth. *Quantitative Economics*, 13(4):1879–1945.

Nickel, C., Bobeica, E., Koester, G., Lis, E., and Porqueddu, M. (2019). Understanding Low Wage Growth in the Euro Area and European Countries. *ECB Occasional Paper No. 232*.

OECD (2011). *Divided We Stand: Why Inequality Keeps Rising*. OECD Publishing, Paris.

Ozkan, S., Song, J., and Karahan, F. (2023). Anatomy of lifetime earnings inequality: Heterogeneity in job-ladder risk versus human capital. *Journal of Political Economy Macroeconomics*, 1(3):506–550.

Puggioni, D., Calderón, M., Cebreros Zurita, A., Fernández Bujanda, L., Inguanzo González, J. A., and Jaume, D. (2022). Inequality, income dynamics, and worker transitions: The case of Mexico. *Quantitative Economics*, 13(4):1669–1705.

Randveer, M. and Staehr, K. (2021). Macroeconomic trends in the Baltic States before and after accession to the EU. In *Does EU Membership Facilitate Convergence? The Experience of the EU's Eastern Enlargement*, pages 211–237. Springer.

Vacas-Soriano, C. (2024). Developments in income inequality and the middle class in the eu. Technical report, Publications Office of the European Union, Luxembourg.

Appendix: For Online Publication

A Additional tables and figures

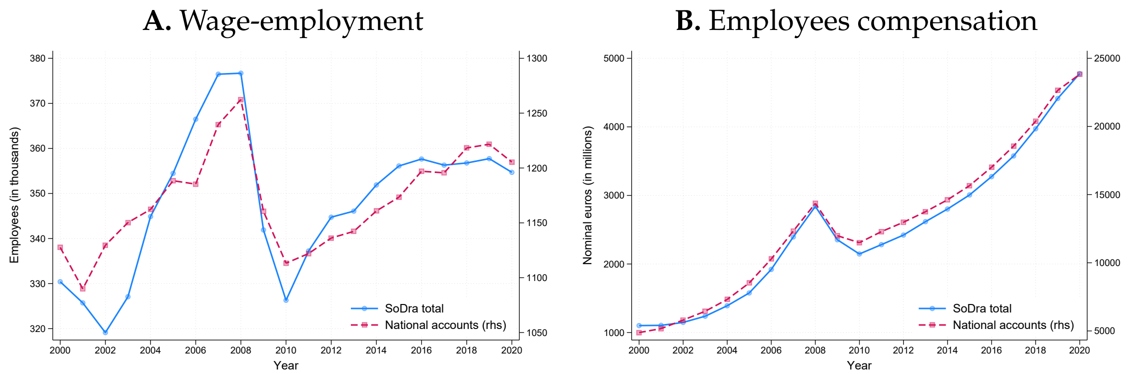


Figure A1: Comparing SoDra to national accounts. *Note*: SoDra total refers to all wage-employees observed in the Social Security sample (Panel A) and the sum of annual earnings received by those workers (Panel B). National accounts correspond to aggregate statistics. Panel A employment stands for all persons engaged in productive activities with a labor contract. In Panel B, compensation of employees is defined as "the total remuneration, in cash or kind, payable by an employer to an employee in return for work done by the latter during an accounting period". *Source*: Eurostat and SoDra, 2000–2020.

A. Annual earnings, minimum wage, and minimum earnings threshold

B. Share of workers with earnings below minimum threshold

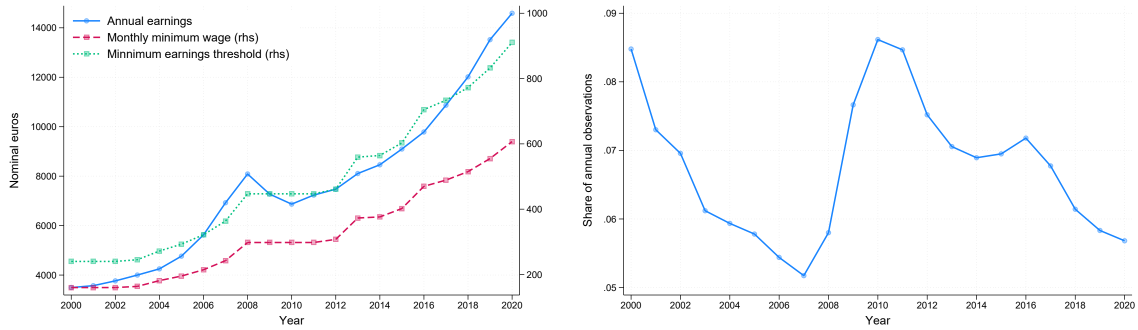


Figure A2: Incidence of minimum earnings threshold. *Note*: Annual earnings stand for the average of all employer payments received by workers aged 25-55 in a given year, while the minimum earnings threshold is defined as 1.5×the monthly minimum wage. *Source*: Statistics Lithuania and SoDra, 2000–2020.

Table A1: Descriptive statistics in selected years by sample type

		Average earnings		Women	Age distribution		
	Individuals	Women	Men	Share	[25,35]	[36.45]	[46,55]
A. CS-sample							
2000	240,112	6,590	7,478	0.538	0.363	0.363	0.274
2005	243,796	8,223	9,600	0.518	0.309	0.356	0.335
2010	230,869	9,854	10,698	0.527	0.335	0.319	0.347
2015	224,575	11,497	13,302	0.496	0.323	0.314	0.363
2020	231,204	16,740	18,530	0.481	0.358	0.308	0.333
B. LS-sample							
2000	161,462	7,098	8,243	0.541	0.414	0.445	0.141
2005	163,257	8,946	11,105	0.533	0.318	0.420	0.262
2010	146,758	10,566	11,768	0.514	0.384	0.425	0.191
2015	150,891	12,476	15,044	0.502	0.350	0.381	0.269
C. H-sample							
2005	138,660	9,591	11,941	0.538	0.267	0.447	0.287
2010	128,541	11,164	12,523	0.515	0.327	0.461	0.212
2015	128,490	13,262	16,086	0.504	0.288	0.412	0.300

Note: CS, LS, and H-samples stand for the cross-section, longitudinal, and heterogeneity samples described in Section 2.2. Earnings are expressed in Euros of 2018.

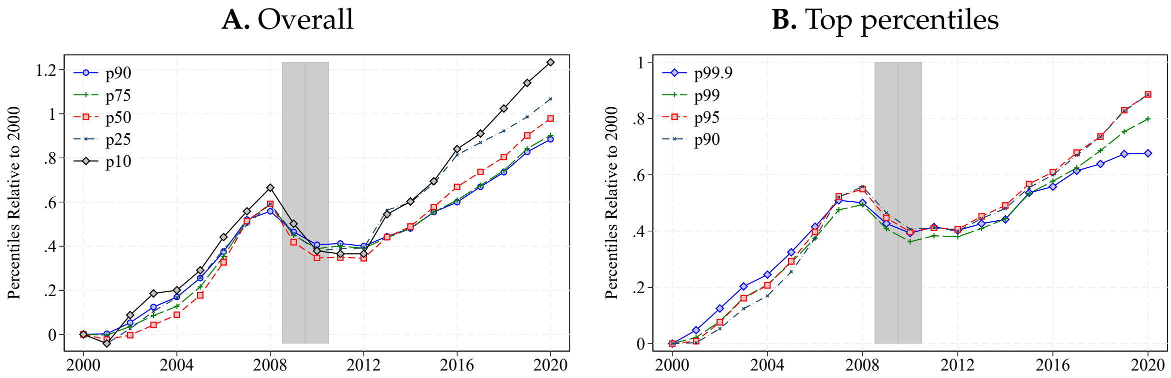


Figure A3: Percentiles of the distribution of log annual earnings, pooled sample. *Note*: *CS*-sample. All percentiles are normalized to 0 in 2000. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

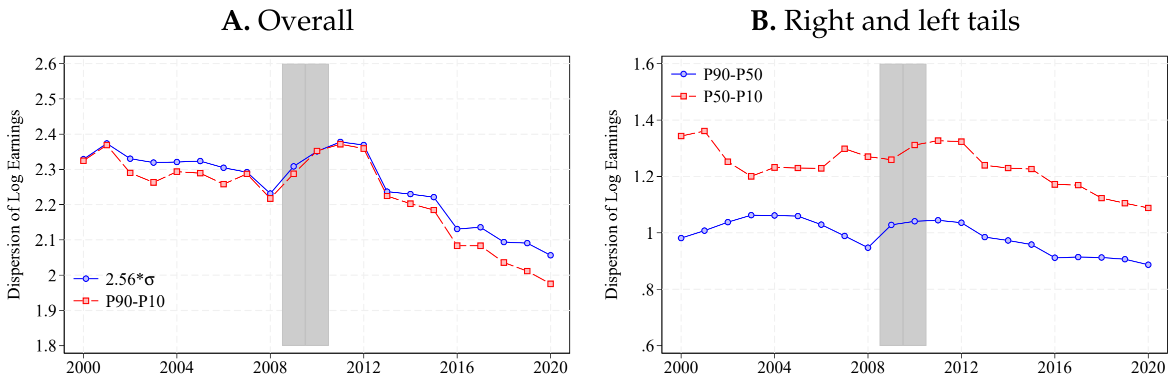


Figure A4: Earnings inequality, pooled sample. *Note*: *CS*-sample, σ denotes the standard deviation of log real annual earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

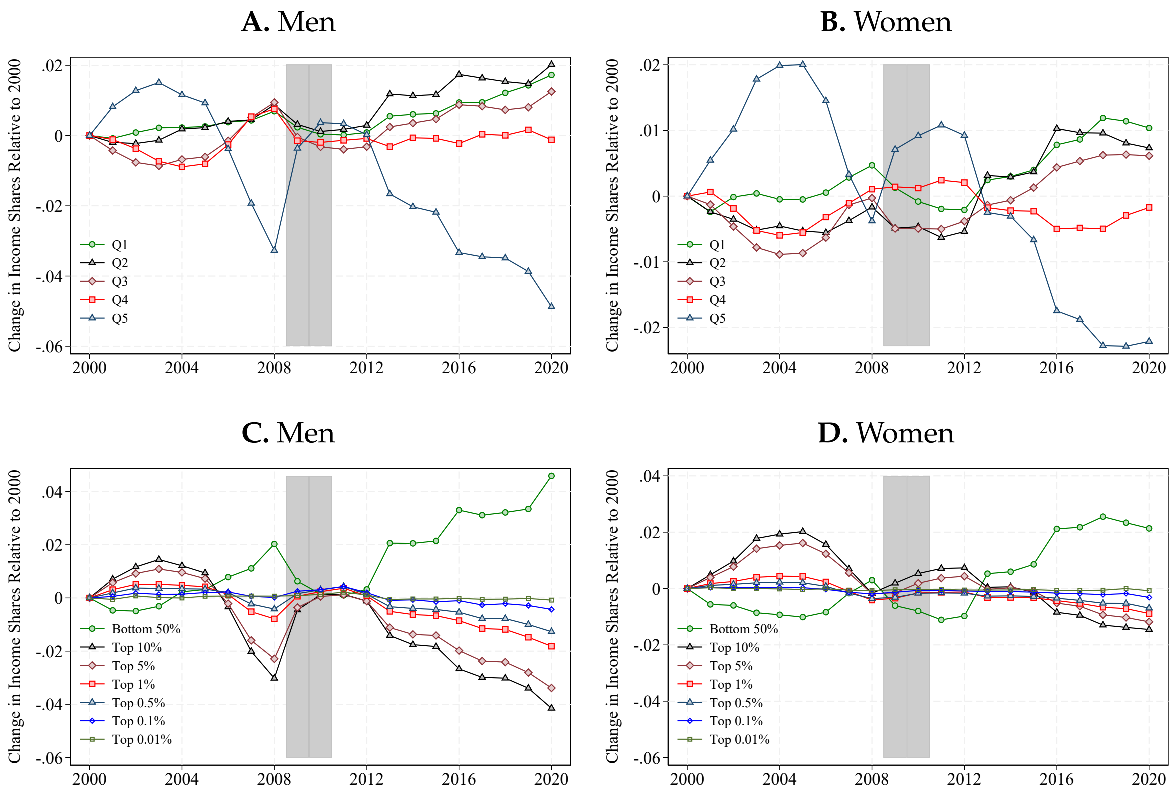


Figure A5: Changes in Income Shares, by gender. *Note*: *CS*-sample. All income shares are normalized to 0 in 2000. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

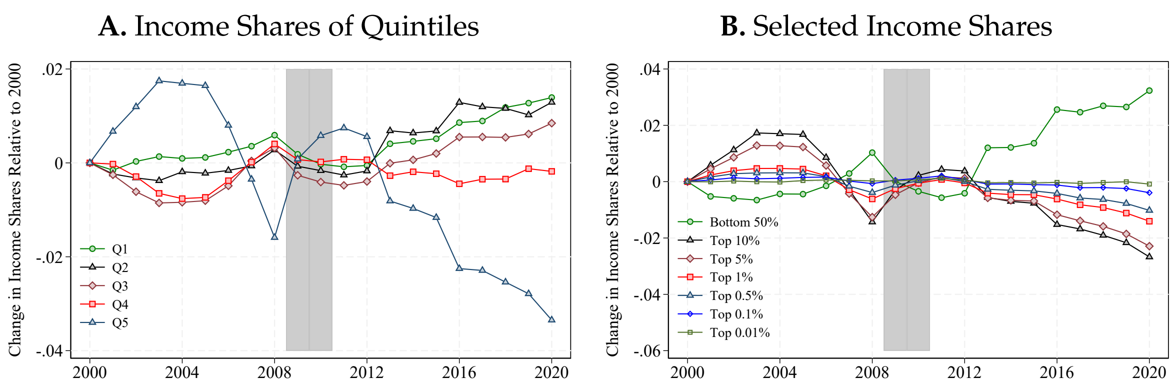


Figure A6: Changes in Income Shares, pooled sample. *Note*: *CS*-sample. All income shares are normalized to 0 in 2000. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

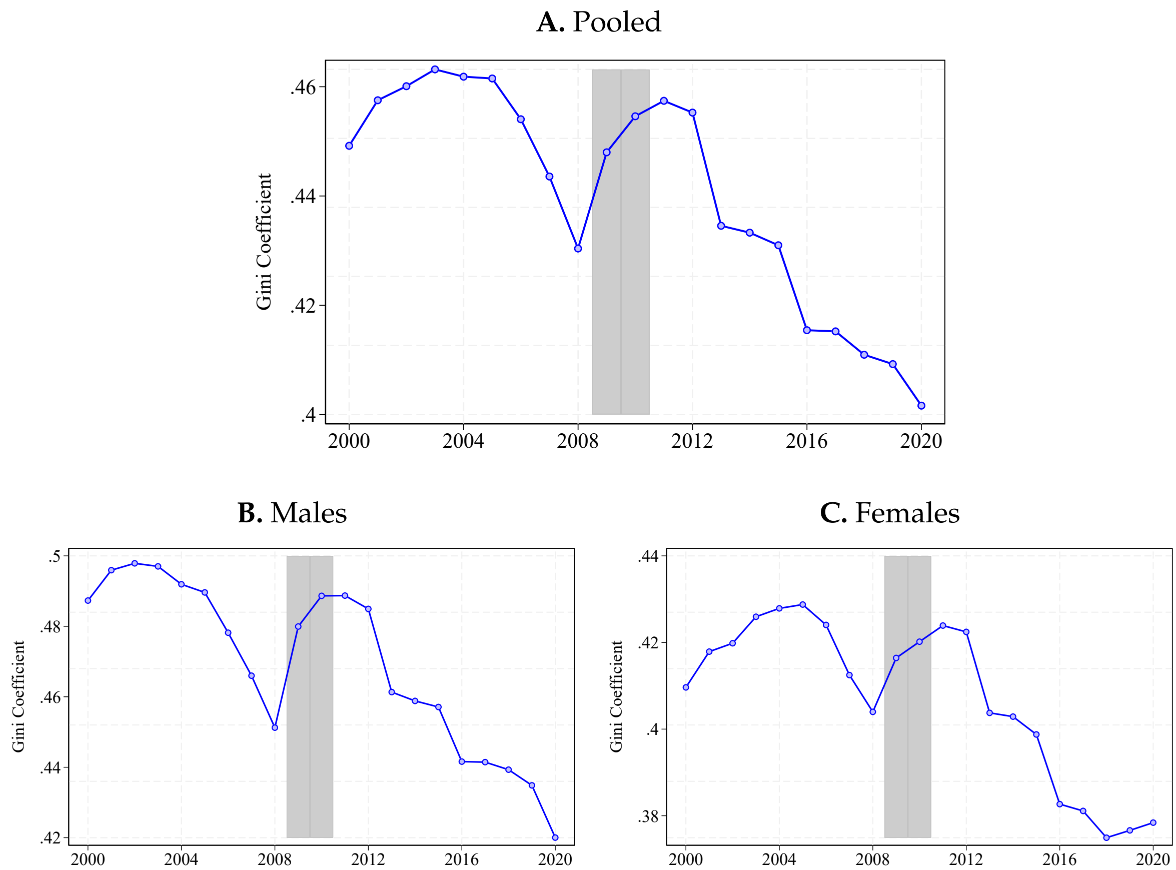


Figure A7: Gini coefficient. *Note*: *CS*-sample. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

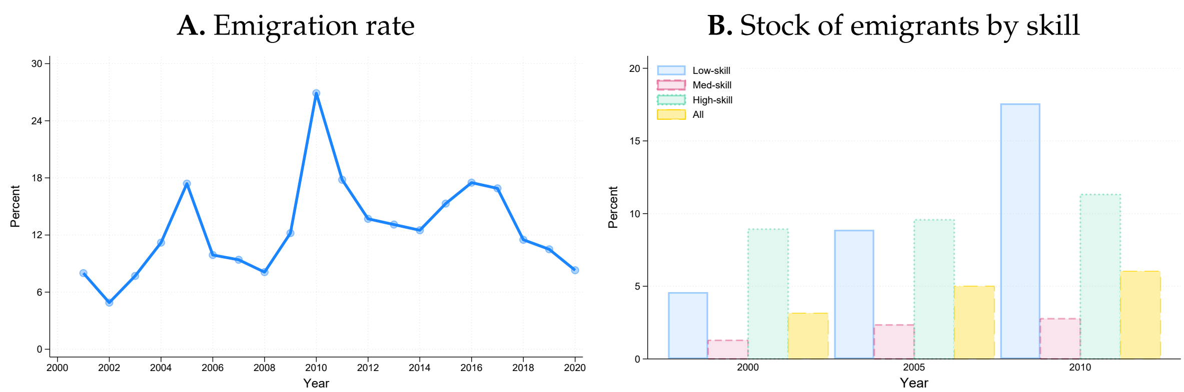


Figure A8: Emigration rate over time and skill levels. *Note*: Emigration rate is the number of emigrants at the end of the year as a percentage of the Lithuanian population at the beginning of the corresponding year. Stock of emigrants by skill refers to the number of Lithuanians aged 25 and over living in Australia, Austria, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom or the United States in a given year as a percentage of the pre-migration population in the destination countries of the same educational level and age in the corresponding year. *Source*: Statistics Lithuania, IAB Brain Drain Data, and own calculations.

Figure A9: Inequality at ages 35 and 45, by gender. *Note*: *CS*-sample, Panels A and B consider only workers aged 35, Panels C and D consider only workers aged 45. *Source*: SoDra, 2000–2020.

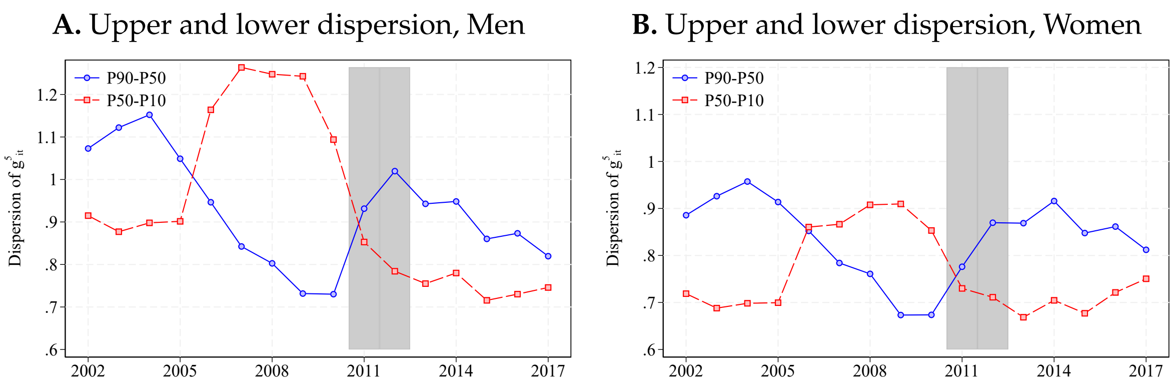


Figure A10: Dispersion of 5-year log earnings changes, by gender. *Note*: *LS*-sample, 5-year changes in residualized log earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

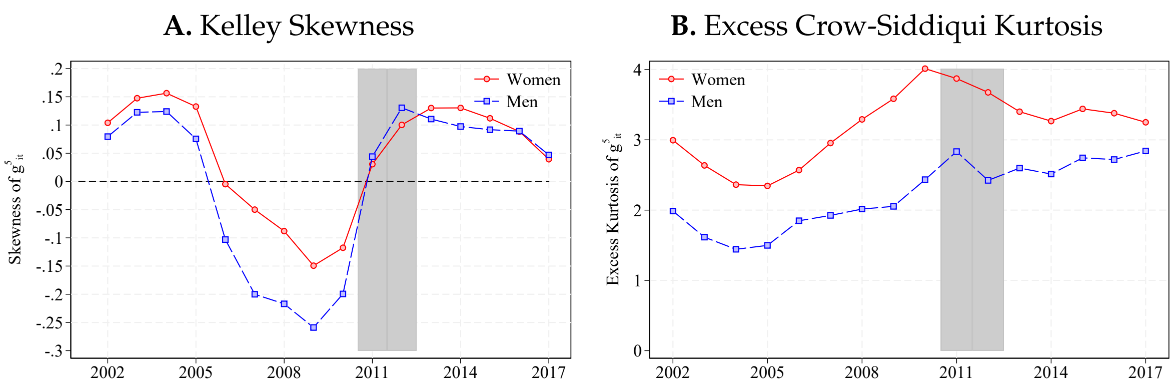


Figure A11: Kelly skewness and excess Crow–Siddiqui kurtosis of 5-year log earnings changes, by gender. *Note*: *LS*-sample, 5-year changes in residualized log earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

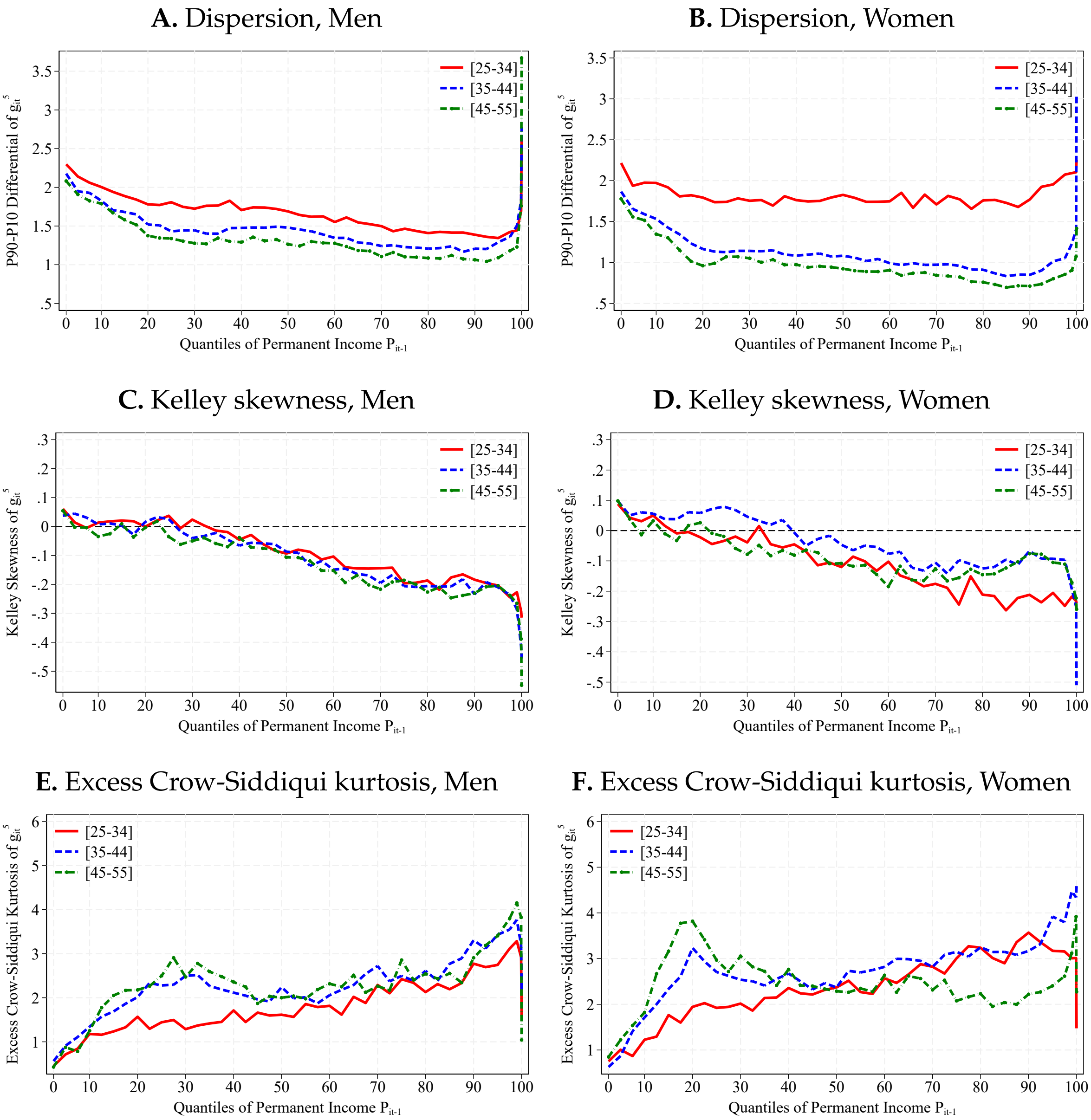
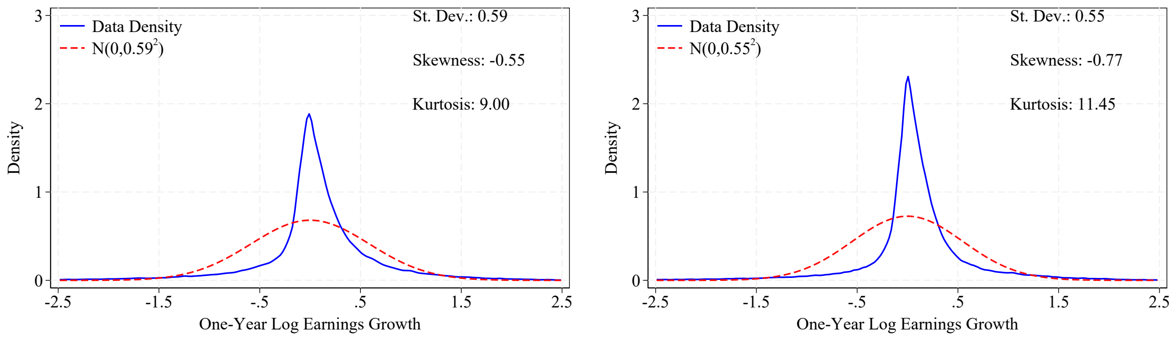
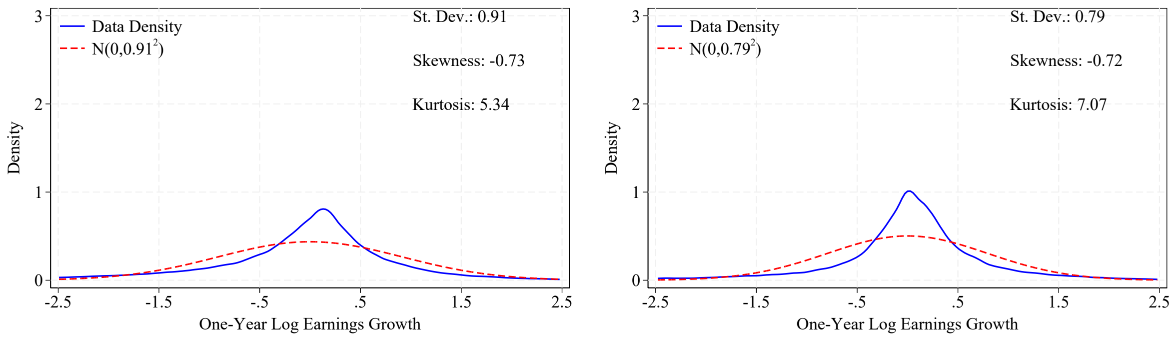


Figure A12: Dispersion, Skewness and Kurtosis of 5-year log earnings changes, by gender, age, and permanent income quantiles. *Note*: *H*-sample, 5-year changes in residualized log earnings. *Source*: SoDra, 2000–2020.



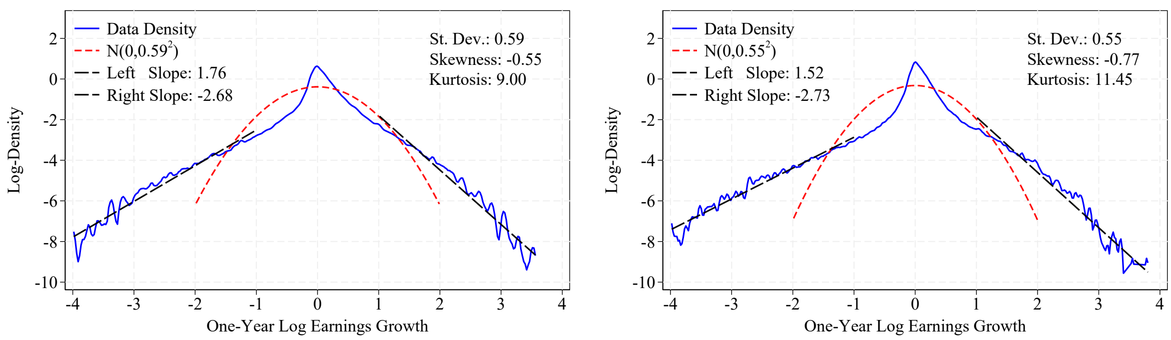
A. Males **B.** Females

Figure A13: Empirical densities of 1-year earnings growth for 2005, by gender. *Note*: *LS*-sample, the density of 1-year log residual earnings growth for 2005. *Source*: SoDra, 2005.



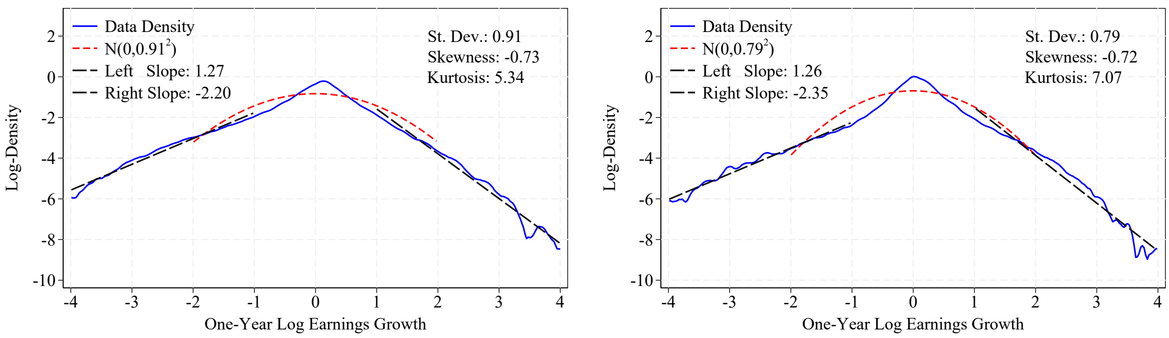
A. Males **B.** Females

Figure A14: Empirical densities of 5-year earnings growth for 2005, by gender. *Note*: *LS*-sample, the density of 5-year log residual earnings growth for 2005. *Source*: SoDra, 2005.



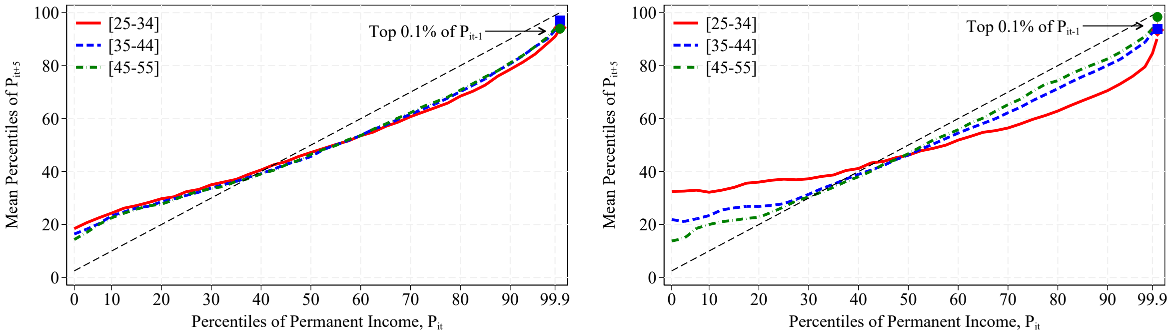
A. Males **B.** Females

Figure A15: Empirical log-densities of 1-year earnings growth for 2005, by gender. *Note*: *LS*-sample, the log-density of 1-year log residual earnings growth for 2005. *Source*: SoDra, 2005.



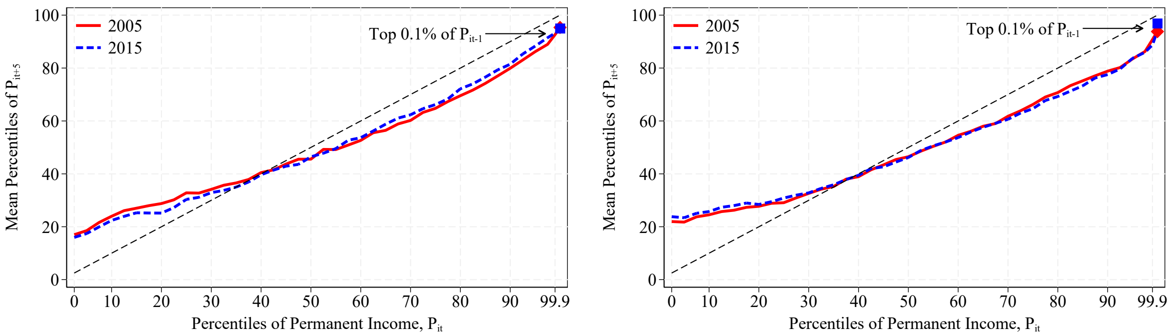
A. Males **B.** Females

Figure A16: Empirical log-densities of 5-year earnings growth for 2005, by gender. *Note*: *LS*-sample, the log-density of 5-year log residual earnings growth for 2005. *Source*: SoDra, 2005.



A. Men **B.** Women

Figure A17: Evolution of 5-year mobility over the life cycle. *Note*: *H*-sample, average rank-rank mobility for men and women of different ages. The black diagonal dashed line is the 45-degree line corresponds to the case of no mobility. *Source*: SoDra, 2000–2020.



A. Men **B.** Women

Figure A18: Evolution of 5-year mobility over time. *Note*: *H*-sample, average rank-rank mobility for men and women, using two alternative base years 2005 and 2015 and averaging over all age groups. The black diagonal dashed line is the 45-degree line that corresponds to the case of no mobility. *Source*: SoDra, 2000–2020.

Table A2: Key statistics on income mobility

A. Pooled, 2002-2020				
	RRS	AUM	ADM	M99
	0.68	33.1	66.9	93.6
B. AUM				
	2002	2007	2010	2015
	33.7	33.0	32.9	33.0
C. AUM Pooled, 2002-2020				
	All	25-34	35-44	45-55
	33.1	36.0	32.5	31.0
D. AUM Pooled, 2002-2020, Men				
	All	25-34	35-44	45-55
	33.1	34.1	32.8	32.3
E. AUM Pooled, 2002-2020, Women				
	All	25-34	35-44	45-55
	33.2	37.8	32.1	29.9

Note: *LS*-sample, 5-year changes in log earnings. RSS: rank-rank slope, defined as the slope coefficient β of the rank-rank regression $R_{it+5} = \alpha + \beta R_{it} + \varepsilon_{it}$; AUM: absolute upward mobility, i.e. expected rank at $t + 5$ conditional on being below the median at time t; ADM: absolute downward mobility, i.e. expected rank at $t + 5$ conditional on being above the median at time t; M99: expected rank at $t + 5$ conditional on being in the top 1% at time t. *Source*: SoDra, 2000–2020

B GRID statistics: Private sector

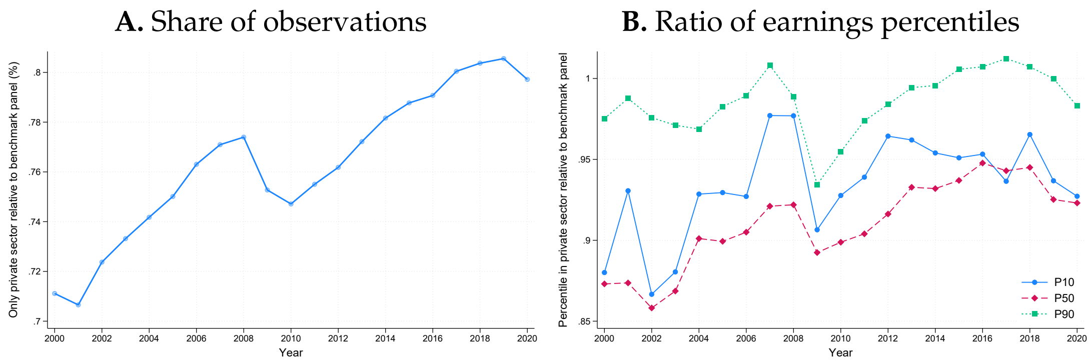


Figure B1: Comparison of worker panel without gaps relative to the baseline panel. *Note*: *CS*-Sample. Panel A shows the share of observations in the private sector relative to the observations in the baseline sample each year. Panel B reports the ratio of earnings percentile is computed as the ratio of the value of a specific earnings percentile of the earnings distribution in the private sector over the value of the same percentile of the earnings distribution in our baseline. *Source*: SoDra, 2000–2020.

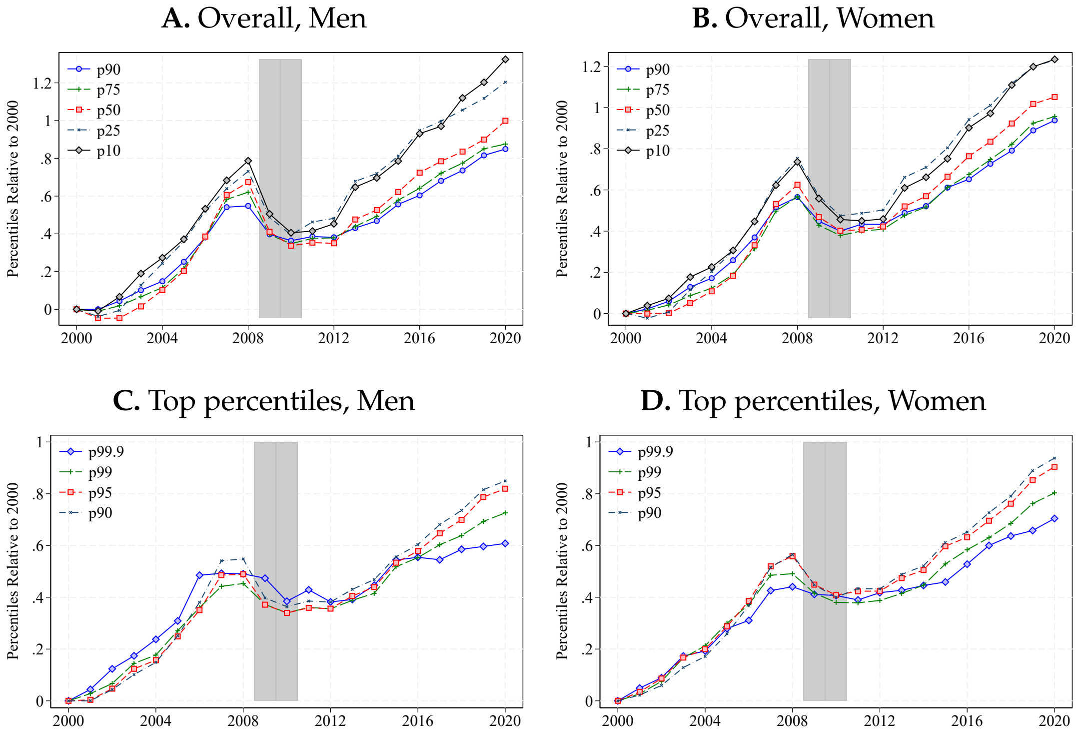


Figure B2: Percentiles of the distribution of log annual earnings by gender. *Note*: *CS*-sample, private sector. All percentiles are normalized to 0 in 2000. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

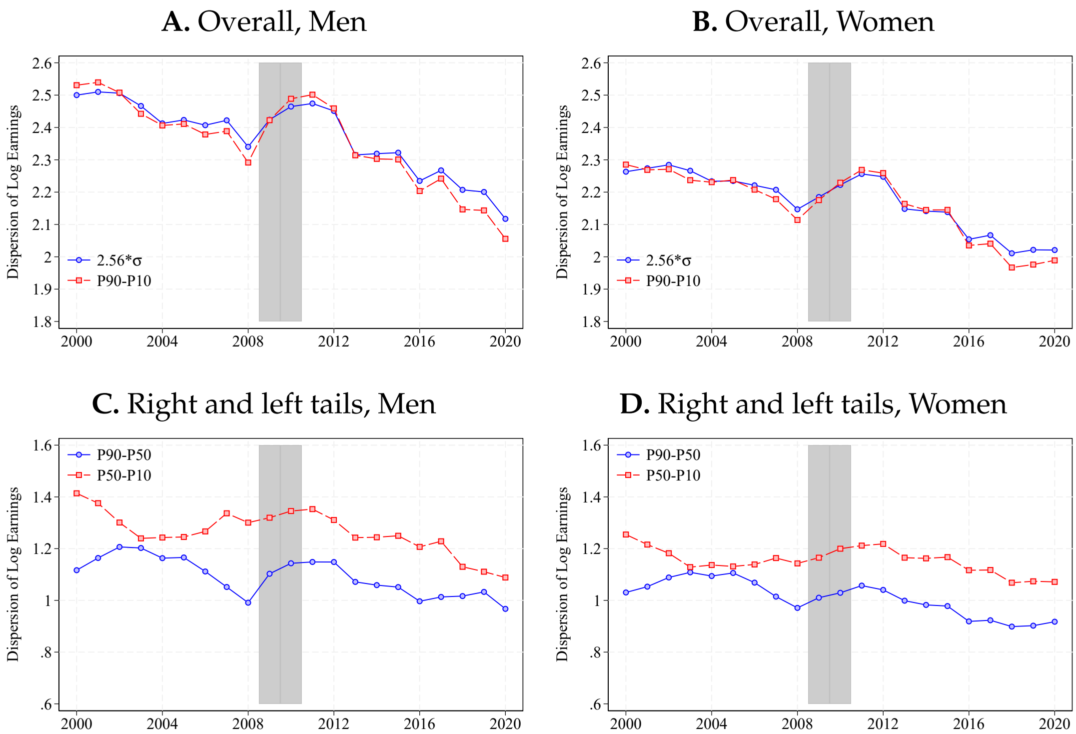


Figure B3: Earnings inequality, by gender. *Note*: *CS*-sample, private sector, σ denotes the standard deviation of log real annual earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

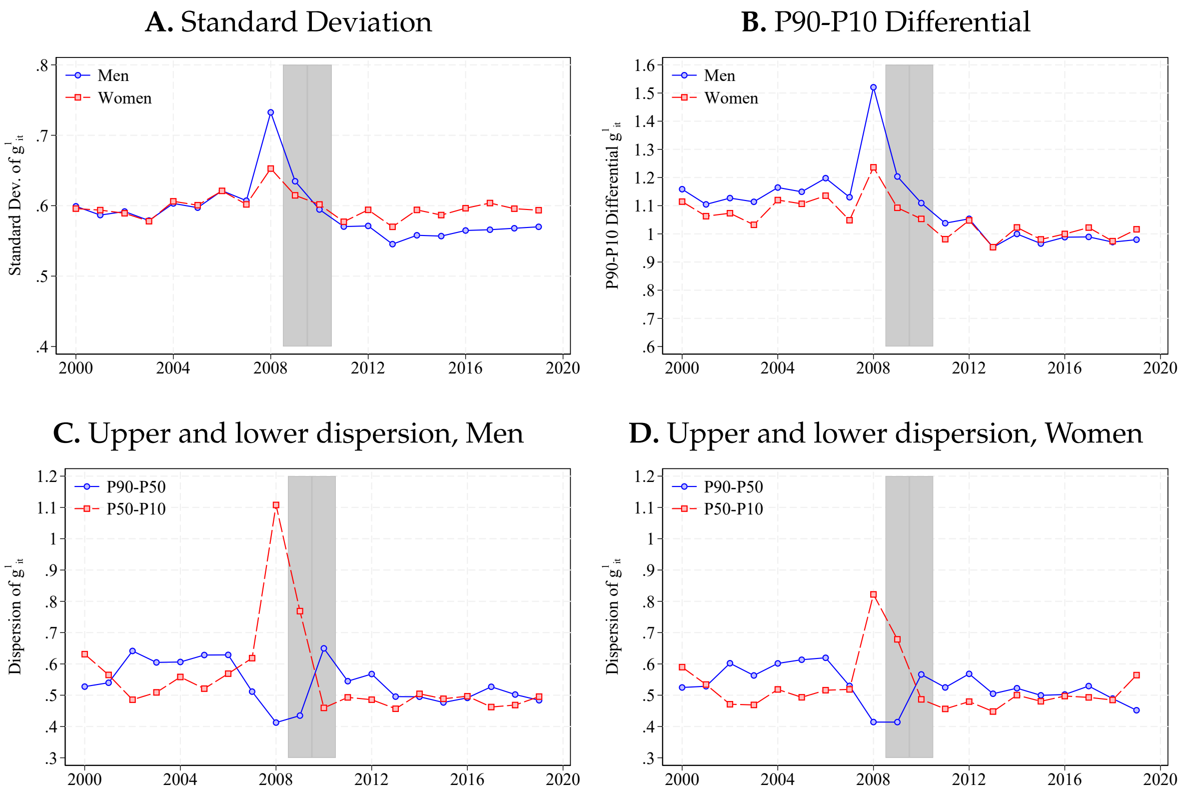


Figure B4: Dispersion of 1-year log earnings changes, by gender. *Note*: *LS*-sample, private sector, 1-year changes in residualized log earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

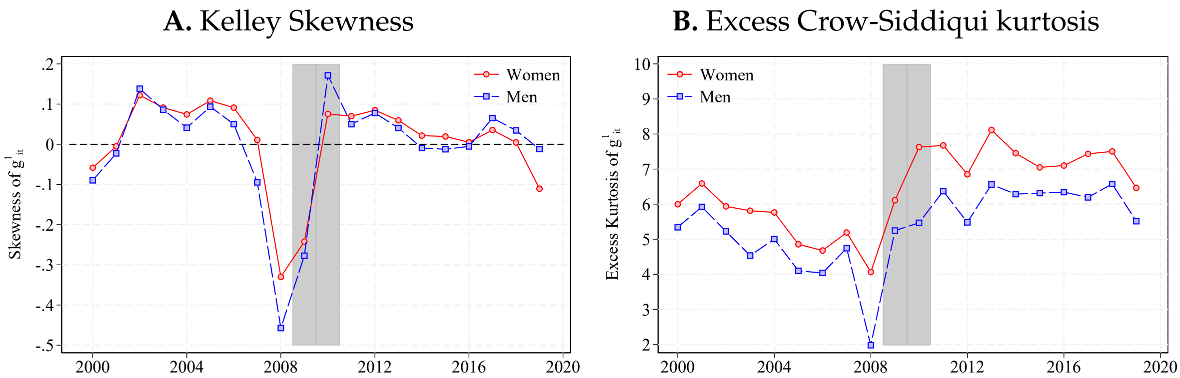


Figure B5: Kelly skewness and excess Crow–Siddiqui kurtosis of 1-year log earnings changes, by gender. *Note*: *LS*-sample, private sector, 1-year changes in residualized log earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

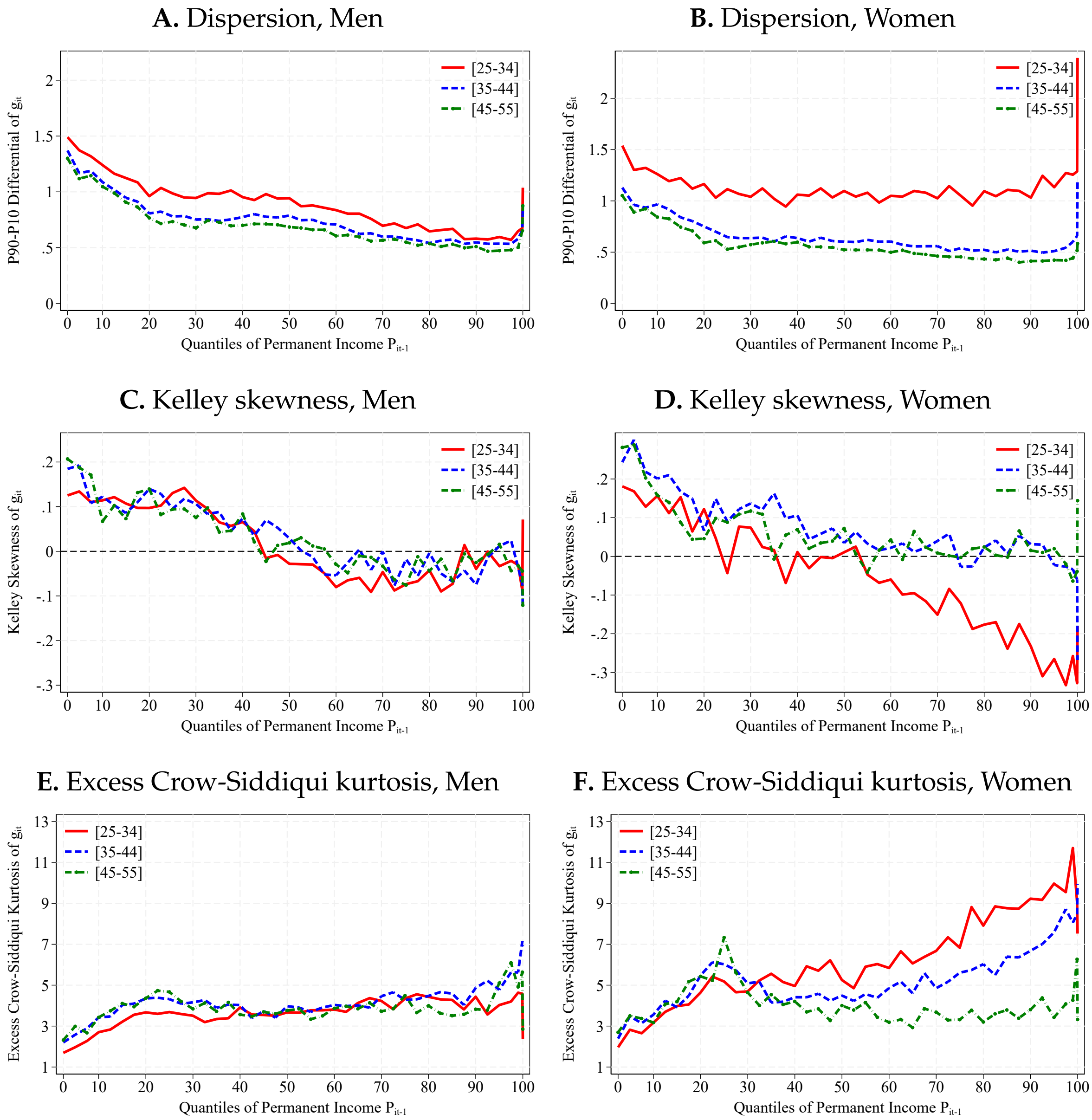


Figure B6: Dispersion, Skewness, and Kurtosis of 1-year log earnings changes by gender, age, and permanent income quantiles. *Note*: *H*-sample, private sector, 1-year changes in residualized log earnings. *Source*: SoDra, 2000–2020.

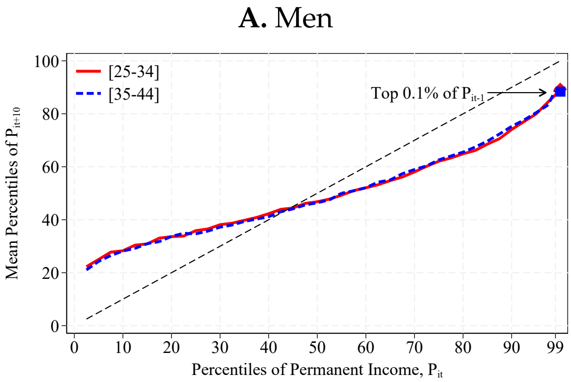


Figure B7: Evolution of 10-year income mobility over the life cycle. *Note*: *H*-sample, private sector, average rank-rank mobility for men and women of different ages. The black diagonal dashed line is the 45-degree line that corresponds to the case of no mobility. *Source*: SoDra, 2000–2020.

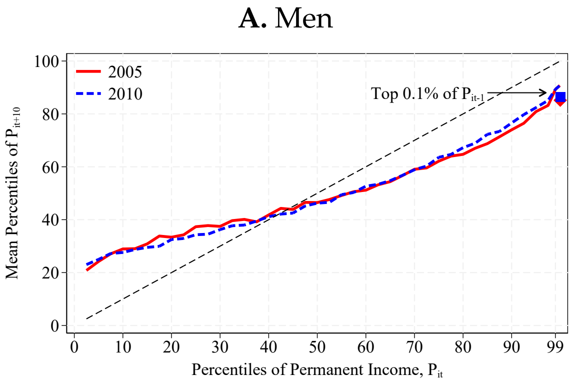


Figure B8: Evolution of 10-year income mobility over time. *Note*: *H*-sample, private sector, average rank-rank mobility for men and women, using two alternative base years 2005 and 2010 and averaging over all age groups. The black diagonal dashed line is the 45-degree line that corresponds to the case of no mobility. *Source*: SoDra, 2000–2020.

C GRID statistics: Panel of workers without gaps

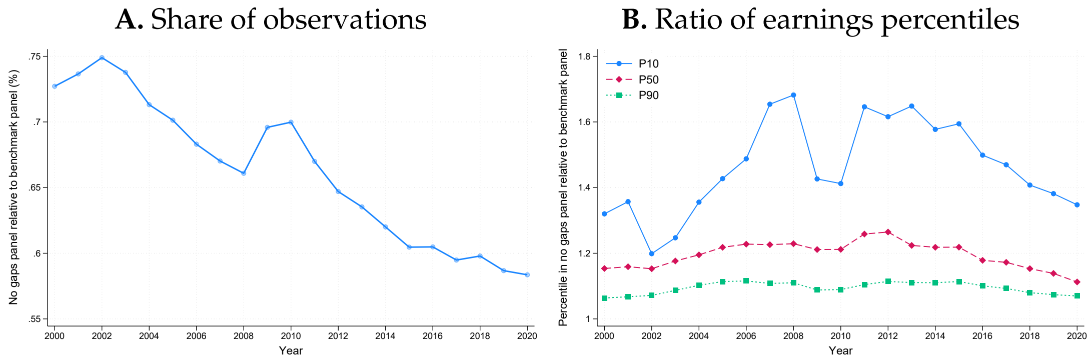


Figure C1: Comparison of worker panel without gaps relative to the baseline panel. *Note*: *CS*-Sample. Panel A shows the share of observations in the panel of workers without gaps relative to the observations in the baseline sample each year. Panel B reports the ratio of earnings percentile is computed as the ratio of the value of a specific earnings percentile of the earnings distribution in the panel of workers without gaps over the value of the same percentile of the earnings distribution in our baseline. *Source*: SoDra, 2000–2020.

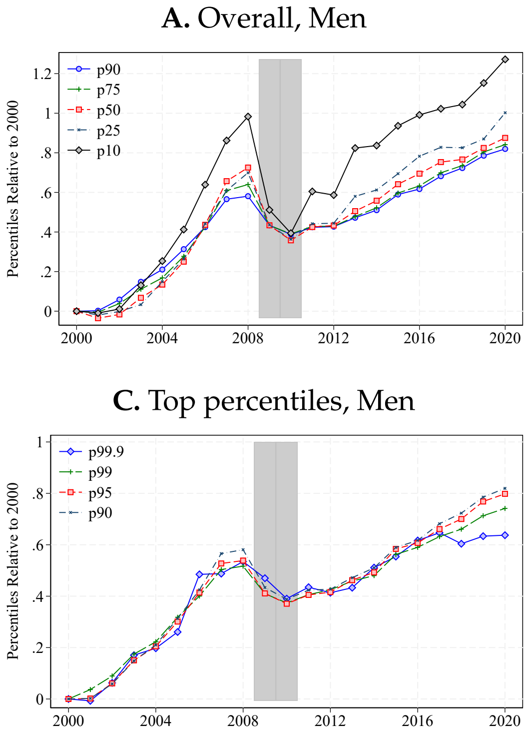


Figure C2: Percentiles of the distribution of log annual earnings by gender. *Note*: *CS*-sample, worker panel without gaps. All percentiles are normalized to 0 in 2000. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

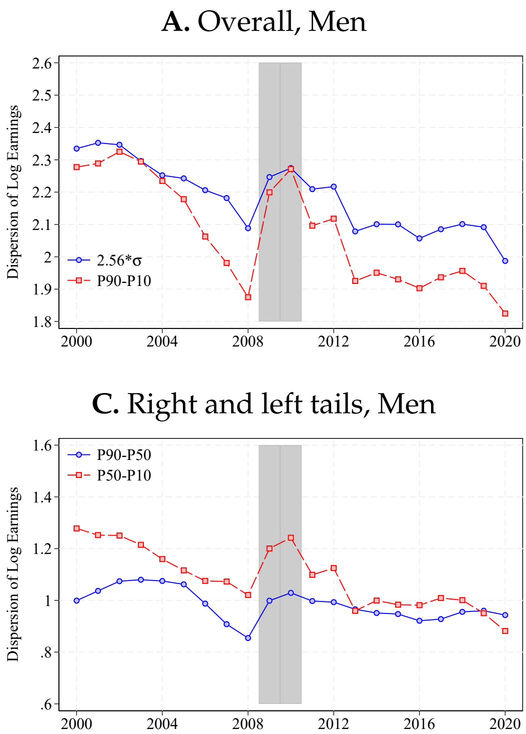


Figure C3: Earnings inequality, by gender. *Note*: *CS*-sample, worker panel without gaps, σ denotes the standard deviation of log real annual earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

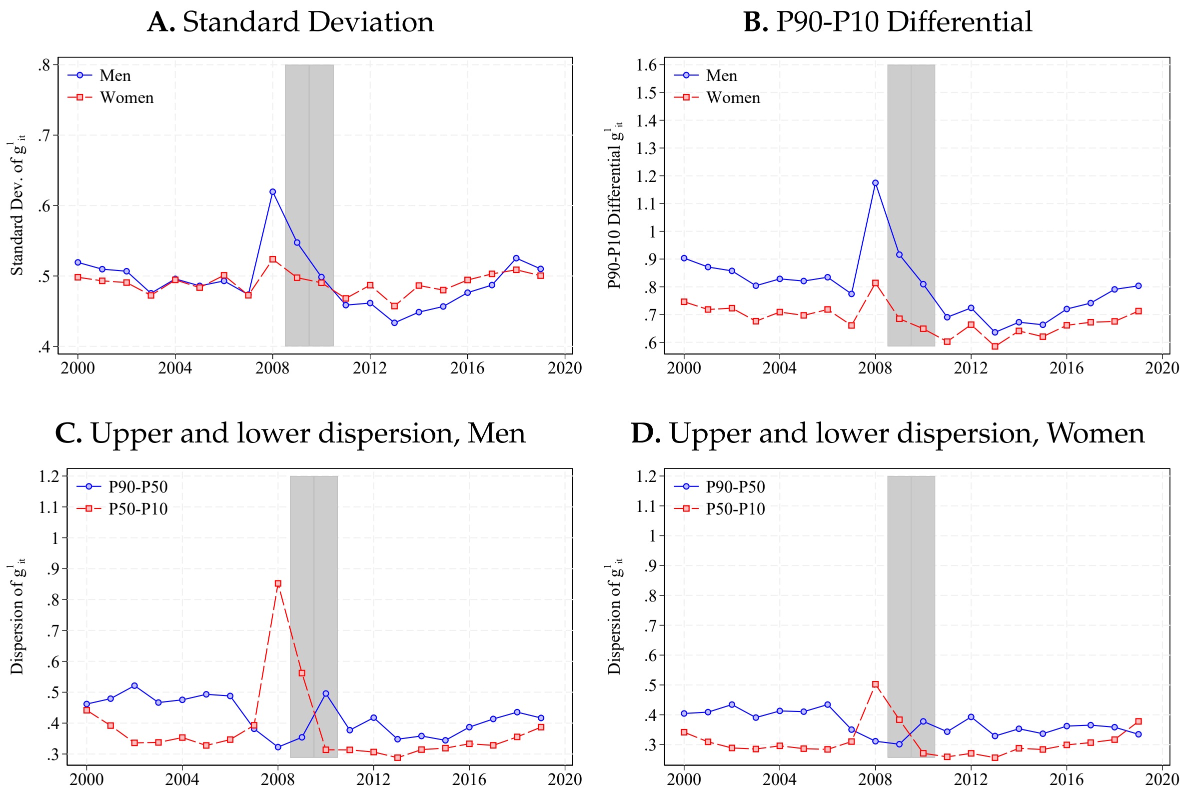


Figure C4: Dispersion of 1-year log earnings changes, by gender. *Note*: *LS*-sample, worker panel without gaps, 1-year changes in residualized log earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

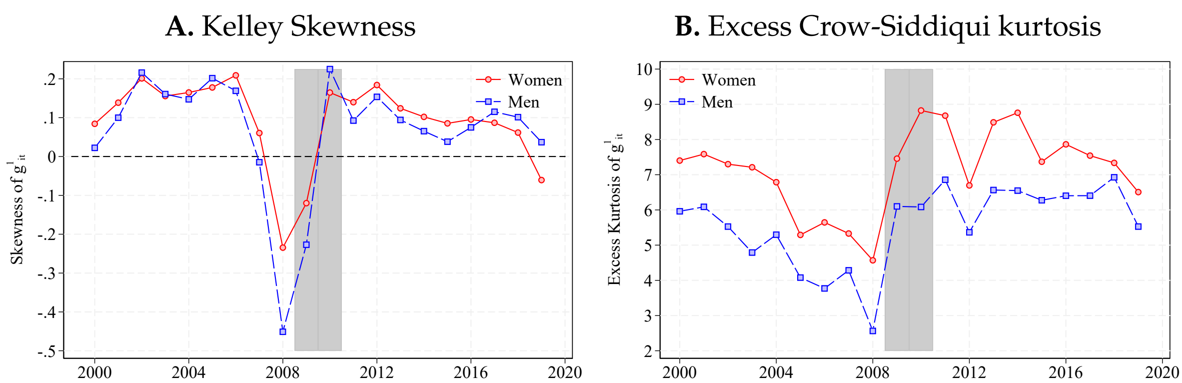


Figure C5: Kelly skewness and excess Crow–Siddiqui kurtosis of 1-year log earnings changes, by gender. *Note*: *LS*-sample, worker panel without gaps, 1-year changes in residualized log earnings. The shaded areas indicate recession years. *Source*: SoDra, 2000–2020.

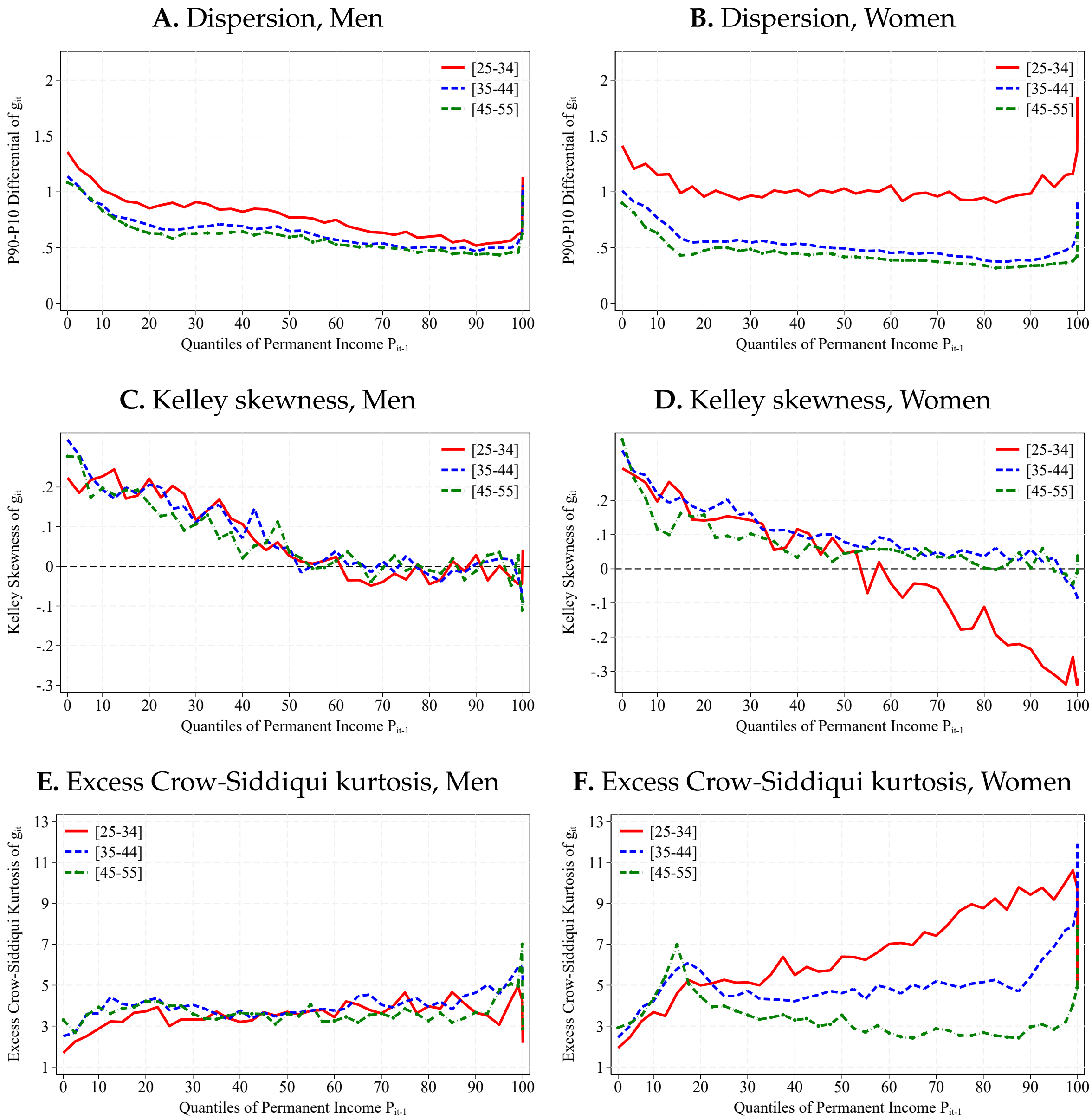


Figure C6: Dispersion, Skewness, and Kurtosis of 1-year log earnings changes by gender, age, and permanent income quantiles. *Note*: *H*-sample, worker panel without gaps, 1-year changes in residualized log earnings. *Source*: SoDra, 2000–2020.

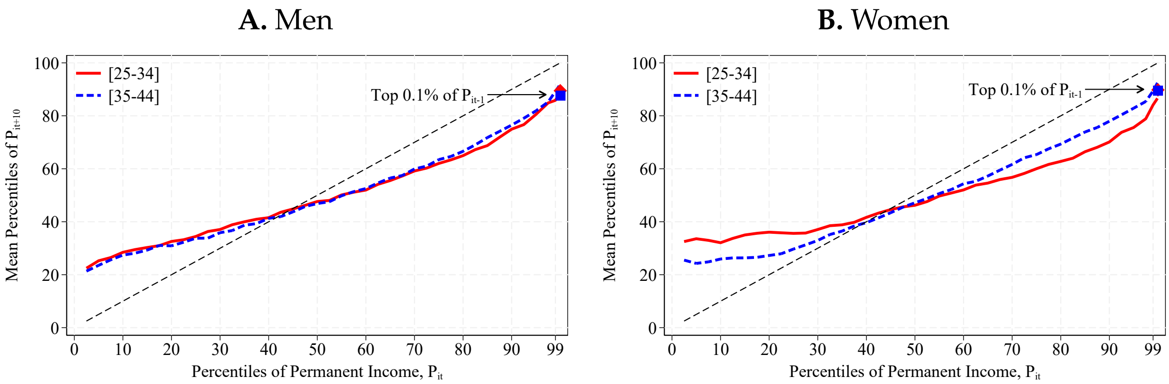


Figure C7: Evolution of 10-year income mobility over the life cycle. *Note*: *H*-sample, worker panel without gaps, average rank-rank mobility for men and women of different ages. The black diagonal dashed line is the 45-degree line that corresponds to the case of no mobility. *Source*: SoDra, 2000–2020.

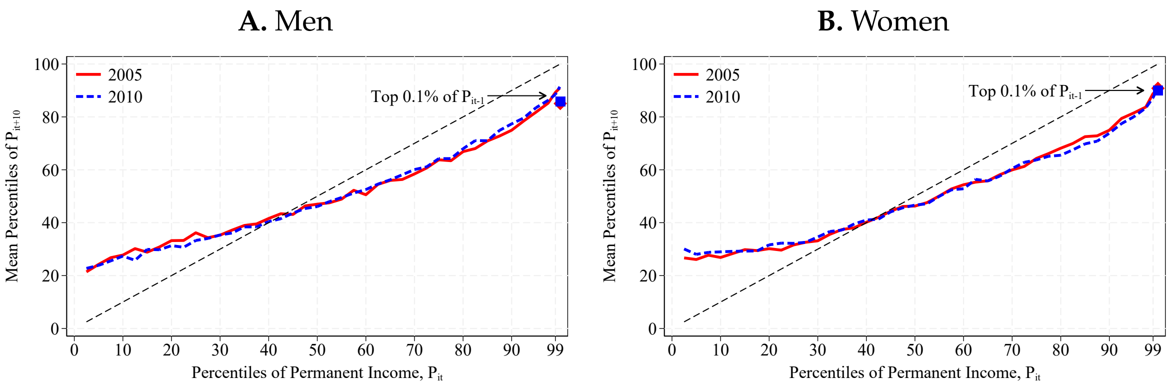


Figure C8: Evolution of 10-year income mobility over time. *Note*: *H*-sample, worker panel without gaps, average rank-rank mobility for men and women, using two alternative base years 2005 and 2010 and averaging over all age groups. The black diagonal dashed line is the 45-degree line that corresponds to the case of no mobility. *Source*: SoDra, 2000–2020.