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A characterization of income dynamics in Poland using administrative data

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A characterization of income dynamics in Poland using administrative data

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Abstract

This paper analyzes earnings dynamics and inequality in Poland from 2000 to 2020 using administrative tax data as part of the Global Repository of Income Dynamics (GRID). Income grew substantially, but inequality was no higher in 2020 than in 2000, having risen through 2006 and fallen thereafter. Earnings changes exhibit pronounced deviations from normality: cyclical skewness, persistent excess kurtosis, and a hockey-stick-shaped dispersion profile across permanent income, steepest at the bottom, flat in the middle, and rising again at the top. We relate percentile-level changes in earnings and earnings growth to the minimum wage, unemployment, and GDP. Minimum-wage growth is strongly associated with gains at the bottom of the cross-sectional distribution and higher unemployment with downward shifts throughout both distributions, while associations with GDP are less stable across specifications. Poland's macroeconomic conditions are related to the location and lower tail of the cross-sectional distribution and to the cyclical asymmetry of earnings changes, while the level of individual earnings risk resembles that of mature European economies.

Keywords:
earnings dynamics, income inequality, earnings risk, administrative data, Poland

JEL Classification:
D31, E24, E32, J31

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1 Introduction

This paper provides a comprehensive analysis of earnings inequality and dynamics in Poland from 2000 to 2020. As part of the Global Repository of Income Dynamics (GRID) project (Guvenen et al. 2022), we compute harmonized statistics using high-quality administrative tax data. The core sample includes the COVID year 2020, but the long-run growth narrative is naturally pre-pandemic: by 2019, real output had doubled relative to 2000 after nearly two decades of uninterrupted growth. While output grew, the labor market exhibited greater fluctuations. The initial period was characterized by a rapid increase in unemployment rates that later receded gradually. By the end of the pre-pandemic period, unemployment was at its lowest since the start of the transition. Poland offers an opportunity to study earnings inequality and dynamics during periods of rapid institutional change and sustained economic growth.

Our paper has two goals. First, we document patterns of earnings inequality, earnings changes, and mobility in Poland following the harmonized framework established by the GRID project, with particular attention to differences between women and men and across the earnings distribution. Second, we examine how annual changes in the cross-sectional earnings distribution and in the distribution of individual earnings changes are associated with changes in the real minimum wage, unemployment, and real GDP. Because this analysis relies on standardized GRID statistics, the same exercise can be implemented in other countries. We interpret the resulting coefficients as descriptive associations rather than causal effects.

The analysis of income inequality shows that the GDP growth experienced by Poland was accompanied by an increase in all percentiles of the earnings distribution. By 2019, the last year before the pandemic, the 90th percentile of real earnings was about 60 log points above its 2000 level for both men and women, and growth at the bottom was larger still: the 10th percentile rose by about 65 log points for men and 80 log points for women. This income growth was achieved without a substantial increase in earnings dispersion. In fact, we document a decline in income inequality after 2006, with the pooled P90-P10 log-earnings gap decreasing by approximately 9.1% (Section 4 reports the corresponding figures separately by gender). The timing of this compression coincided with rapid minimum-wage growth and a tightening labor market.

Turning to earnings dynamics, we document that in spite of the decline in cross-sectional inequality, the dispersion of individual earnings changes remained remarkably stable throughout the period. As in other countries, the distribution of annual earnings changes exhibits pronounced deviations from normality. We document cyclical skewness and persistent excess kurtosis. Skewness is positive in expansions, especially for women, and turns negative during periods of high(er) unemployment. High excess kurtosis indicates that most workers experience modest changes while a minority face very large changes. These changes are not evenly distributed across the income distribution. In fact, our results reproduce the hockey-stick pattern documented in other GRID countries: dispersion is highest at the bottom, declines through the middle of the distribution, and rises again at the top (see Drechsel-Grau et al. 2022, Kramarz et al. 2022, Halvorsen et al. 2022, Leth-Petersen and Sæverud 2022, to name a few).

Our data reveal substantial heterogeneity in earnings risk by gender and age. Young women exhibit higher earnings volatility and more pronounced downward mobility at higher income levels, patterns consistent with labor market interruptions associated with family formation (Cukrowska-Torzewska 2015). Five-year mobility statistics reveal upward mobility at the lower tail of the income distribution, whereas at the top income ranks tend to be more persistent.

To connect these distributional patterns to Poland's macroeconomic experience, we examine how changes in the real minimum wage, unemployment, and real GDP co-move with different parts of the earnings distribution. Using annual GRID statistics, we estimate percentile-level regressions for two distinct outcomes: changes in the cross-sectional percentiles of log real earnings and percentiles of the distribution of individual earnings changes. This approach allows us to distinguish shifts in the location of the distribution from changes in its dispersion and tails. Because the analysis relies on contemporaneous aggregate variation over a relatively short period, we interpret the estimates as descriptive associations rather than causal effects.

Growth in the real minimum wage is strongly associated with increases in lower earnings percentiles, with the coefficients declining toward the top of the distribution—a pattern consistent with cross-sectional earnings compression. Rising unemployment is associated with declines across the earnings distribution and with a leftward shift in the distribution of individual earnings changes. The relationships with GDP growth are generally estimated less precisely. An accounting decomposition further indicates that the fitted component associated with the three macroeconomic variables tracks changes in the dispersion of earnings growth more closely than changes in skewness or kurtosis. Together, these results connect Poland's distinctive macroeconomic developments to changes in the location and shape of its earnings distribution without imposing a parametric income process.

The remainder of the paper is organized as follows. Section 2 provides background on the Polish economy, focusing on macroeconomic performance, labor-market transformations, the minimum wage, and the informal economy. Section 3 describes the administrative tax data and compares them with survey data. Section 4 documents earnings inequality, the distribution of earnings changes, and earnings mobility. Section 5 examines how these distributional outcomes are associated with changes in macroeconomic conditions in Poland. Section 6 concludes.

2 Polish Background

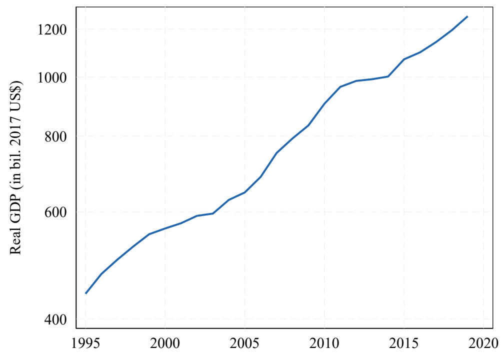
Macroeconomic landscape Poland experienced a period of uninterrupted GDP growth, as shown in Figure 1a. By the end of 2019, real GDP was twice as large as in 2000, implying an average annual growth rate of around 4 percent. To place this in context, this growth rate appears to exceed that of other Visegrad countries (Czechia, Hungary, and Slovakia) and to fall only slightly below that of the Baltic countries, whose economies are substantially smaller. Part of the growth may reflect a reduction in the shadow economy. Estimates in Cichocki and Torój (2023) suggest a decline of the shadow economy from around 20% of GDP in 2000 to 8% in 2019.

As shown in Figure 1b, growth accelerated in the years immediately following EU accession. EU membership improved access to the common market and brought additional funds through the cohesion policy implemented by the European Union. Hagemejer et al. (2021)'s counterfactual model estimates that Polish GDP would be between 20% and 30% lower absent EU accession. Grassi (2024)'s model similarly estimates that the gains from accession are comparable to those accrued to other central and eastern European countries, attributing them to both a reduction in misallocation across firms and to productivity increases.

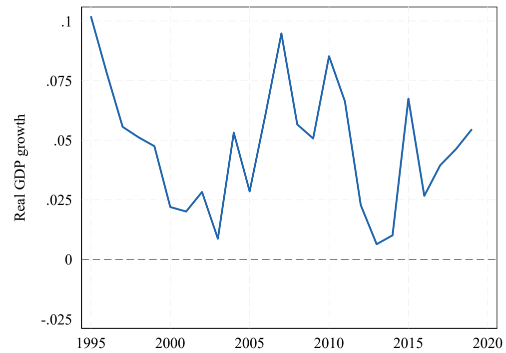
Unlike many European countries, Poland did not experience a recession in the aftermath of the Lehman Brothers collapse. Growth nevertheless weakened during this period, and particularly in the aftermath of the Euro crisis. The first GDP contraction occurred in 2020 during the COVID pandemic and reflects policy responses such as lockdown measures. Real GDP resumed growth in the subsequent year.

This GDP growth was accompanied by a dynamic labor market. Figure 1c plots the evolution of registered unemployment as a percentage of the active population. Three periods are clearly visible in the registered series. First, up to 2003-2004, registered unemployment increased markedly, reaching around 20% of the workforce at its peak. This percentage declined rapidly in the second half of the 2000s until the Euro crisis, when it stabilized. Several factors contributed to the decline in registered unemployment. The first possible explanation is migration. Between 2004 and 2008, the number of temporary migrants

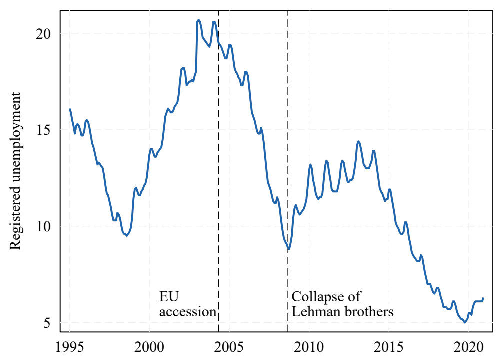
Figure 1: Evolution of macroeconomic indicators



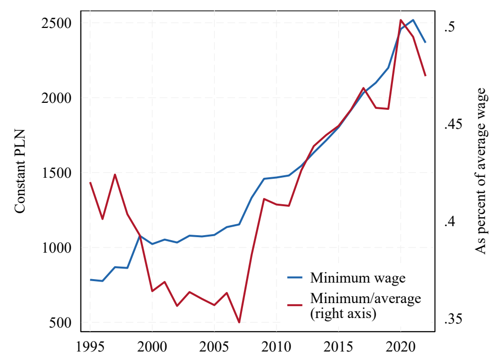
(a) GDP in constant prices



(b) GDP growth



(c) Registered unemployment



(d) Evolution of minimum wages

Notes: Panels (a) and (b) show GDP in constant US$ (2017) and annual growth rates; data from Penn World Tables (Feenstra et al. 2015). Panel (c) shows registered unemployment as a percentage of the active population based on monthly data from the Central Statistical Office (GUS). Panel (d) shows the minimum wage in constant PLN (2018) and as a fraction of average wages.

increased by about a million individuals, the largest migration during peaceful times for Poland—a figure comparable to roughly half of the decline in the number of unemployed individuals during that period. Migration was, however, also common among the employed and the inactive, and not only among the unemployed. According to Budnik (2007), in the years following the accession period employed individuals represented 40% of outward migration, and the remaining sixty percent were evenly split between unemployment and inactivity. Taken at face value, this implies that only around 30% of the roughly one million migrants, or approximately 0.3 million individuals, came directly from unemployment—a comparatively modest share of the decline in the number of unemployed. It is not possible with existing data to evaluate what happened to the jobs left by emigrants, whether they translated into additional opportunities for inactive or unemployed workers. In that case, emigration could have had an indirectly effect in unemployment. Alternatively, if emigrants left were precarious jobs, i.e. likely to be terminated, outward migration could have prevented an increase in unemployment. While likely, these links remains speculative. The comprehensive research in Kaczmarczyk and Okolski (2008) failed to find a significant relationship between the unemployment rate and emigration using regional data.

The main drivers of the decline of unemployment are related to job creation (Budnik 2007, Lewandowski and Magda 2023) and demographic trends (see Biagi and Lucifora 2008, for an analysis across European countries). Demographic trends are one proposed contributor: the cohort size of labor market entrants in 2005–2010 was smaller than in previous years for two reasons. First, the number of births in 1980 was 695 thousand, while by 1990 it has declined to 548 thousand, a 20% decline. Moreover, these cohorts entered the labor market later, as they were more likely to complete tertiary studies (Lewandowski and Magda 2023). Simultaneously, those years saw the (early) retirement of older and more numerous cohorts (see Chlon-Dominczak 2009, for an account of retirement patterns, particularly early retirement in Poland). After 2015, a second period of rapid decline in registered unemployment began. By 2019, the last pre-pandemic year, unemployment was among the lowest since the early 1990s.

Even if unemployment movements reflect changes in the extensive margin, i.e. relative cohort size, we expect that periods of reduced employment intensity affect earnings dynamics. Mechanically, working fewer months in a given year translates into lower annual earnings. We expect that periods of lower employment are reflected in declining bottom percentiles. Moreover, periods of unemployment can affect wage dynamics as well. To illustrate this idea consider a worker on a full-time contract in years $t-1$ and $t+1$ who experiences an unemployment spell in year t. This spell produces both a negative income shock between periods $t-1$ and t, and a positive shock between periods t and $t+1$, even if the hourly wages are constant throughout the three-year period. This mechanism reflects the insights from Hoffmann and Malacrino (2019) and Hoffmann et al. (2022), who showed that non-voluntary job separations are associated with greater income uncertainty.

Transition to a market economy A defining feature of Poland was the transformation of its economy from a centrally planned to a market economy. This transformation implied two simultaneous transitions: from state-owned enterprises to private firms, and from manufacturing to the service industry. While the privatization of SOEs took place throughout the 1990s and early 2000s, two years stand out as particularly active: 1997 and 2001. One would expect these years to be characterized by increased unemployment, yet this is not evident in Figure 1c: there is no spike in either year. Cichocki et al. (2017) analyze quarterly data and show that the decline in public sector employment was accommodated mostly through flows into and out of inactivity: the entry of younger workers and the retirement of older workers. The net demographic effect was negative, partly reflecting international migration of young, talented workers.

Exploring worker flows from the public to the private sector, it appears that they occurred mostly within industries (Cichocki et al. 2017), suggesting that either newly privatized firms retained a substantial portion of their employees, or workers did not experience difficulties finding new jobs in the private sector. The fact that misallocation dragged down economic growth for several years (see Hagemejer et al. 2018) is indicative of the first mechanism: privatization without reallocation.

Minimum wage The minimum wage is an important policy instrument in Poland. Each year, the national government proposes its value to the Social Dialogue Council, a tripartite body that includes business representatives and trade union members. New minimum wages are announced no later than September and become binding in January of the following year. In setting minimum wages, the council considers both projected inflation and GDP growth for the coming year. The national minimum wage is a statutory floor that applies to employees generally, in both the private and public sectors; certain occupations (e.g., doctors and teachers) are additionally covered by sector-specific pay scales negotiated above this floor (Majchrowska and Strawiński 2024). The minimum wage also has a mechanical impact on wages above its level, as some pay components are pegged to its value (e.g., compensation for night shifts).

The evolution of the minimum wage is presented in Figure 1d. The figure shows the value of the minimum wage for full-time employees in constant PLN (2018) and the bite of minimum wages. The evolution of minimum wages mirrors that of GDP growth: by 2022, real minimum wages had tripled relative to 1995. Considering the years after 2008, Poland has been among the EU countries with the largest increases in minimum wages (Albinowski and Lewandowski 2021). The minimum wage bite was initially high but did not catch up with average wages during periods when unemployment rose. Since 2010, growth in minimum wages has outpaced that of average wages. In terms of employment, estimates suggest that around 10% to 16% of workers in the private sector earn minimum wages; in the public sector, the proportion is an order of magnitude smaller at 1.5% (Majchrowska and Strawiński 2024). For the economy as a whole, the proportion of minimum wage workers was estimated at 12% in 2018.

Previous analyses (Kamińska and Lewandowski 2015, Albinowski 2018) show that minimum wage increases have a small but negative effect on employment. The lack of stronger employment effects has been attributed to switches to contracts that are less onerous to employers, such as temporary positions or civil contracts (Kamińska and Lewandowski 2015). The employment effects for Poland are comparable to those found in other developing countries (see the meta-analysis of Broecke et al. 2017). Bodnár et al. (2018) discuss minimum wage adjustments from the perspective of firms, and show that firms prefer strategies other than lay-offs, such as cutting other costs. Firms adjust hiring rather than dismissing existing staff. To some extent, the prevalence of envelope wages among low earners may also help explain the muted employment response.

Compliance with minimum wage legislation is not perfect. Using survey data from 2003 to 2012, Goraus-Tańska and Lewandowski (2019) estimate that around 4% of workers receive wages below the minimum wage level. Poland ranks fourth among Central and Eastern European countries in terms of violation frequency, behind Lithuania, Latvia, and Hungary. Goraus-Tańska and Lewandowski (2019) show that minimum wage violations are stable across years, and are more common for hourly than for monthly wages. Our database is then unlikely to capture these minimum wage violations, and our statistics can understate recorded earnings fluctuations.

Given that around 10 percent of formal workers earn minimum wages, and the small or regionally concentrated employment effects identified in the literature, we expect that periods of rapid minimum wage growth will match periods of rapid growth at the lower end of the income distribution. Since several compensation components are indexed to the minimum wage, increases in it may also generate spillover effects further up the income distribution.

The informal economy The informal economy poses a challenge for the analysis of wage dynamics based on tax reports. In Poland, we observe two elements, unregistered workers and envelope wages. Cichocki and Tyrowicz (2011) measure unregistered work using the labor force survey. They measure unregistered work as the proportion of workers who also receive unemployment benefits.[1] They show a decline in unregistered work from around 2% of total employment in the mid-1990s to less than 0.8% in 2010. Similarly low numbers are reported in more recent work (Nikulin and Sobiechowska-Ziegert 2018, Liwiński 2022). The prevalence of informal work varies across individual characteristics (more common among youth) and regions (more common in less developed areas). Given this low prevalence, this particular form of simultaneous registered unemployment and undeclared work does not appear to be a serious concern for our estimates of earnings dynamics; we note, however, that this is a narrow proxy for informality, and that Liwiński (2022) also considers work

[1]Workers with a registered employment contract cannot claim unemployment benefits.

performed without a written agreement as a distinct measure.

Envelope wages describe cases where wages declared to the tax authority fall short of wages actually received by the worker. These arrangements benefit both employees and employers, since both parties avoid paying taxes and social security contributions. Using 2018 data, Kośny et al. (2024) estimate that between 10% and 11% of workers under employment contracts receive part of their income as envelope wages. These arrangements are more common among those employed in private firms, and among workers whose earnings hover around the minimum wage. At the intensive margin, Kośny et al. (2024) compute that wages would be on average 5% higher if envelope payments were included.

The prevalence of envelope wages can bias our estimates of earnings levels and earnings dynamics in different ways. First, a secular decline in the prevalence of envelope wages—a shift from undeclared to declared pay—can overstate genuine earnings growth at the bottom of the distribution, where envelope wages are most common: part of the measured increase in lower percentiles may reflect a growing propensity to declare income rather than a change in total compensation. Second, and separately, to the extent that envelope wages are a more flexible component of pay that is only partly captured in the tax data, omitting them can lead us to underestimate the variance of individual earnings growth. We do not attempt a formal correction for either bias here.

3 The Personal Income Tax data

The analysis is based on tax records obtained for the period 2000–2020. The data are gathered by the Ministry of Finance on the basis of declarations made by both employers and employees. The employer is responsible for the initial declaration. Every month, the employer pays social security contributions and income taxes on behalf of the worker to ZUS and the tax office. The concept of earnings in PIT data includes all payments related to a given employment relationship. It comprises regular wages, additional payments (bonuses and premiums), and other employment-related payments where applicable. Earnings are not censored. At the beginning of every year, the employer sends to the worker a summary of all payments made on their behalf in the previous year. Having received this document, the worker submits to the Ministry of Finance a consolidated return reporting income from all employment positions held during the year. In their declaration, workers can apply for various tax reliefs, e.g. those connected with children, heating expenses, etc.

Workers submit one declaration for each source of income (wage income, self-employment, capital gains, rental). It is, however, rare for a worker to declare more than one source of income: only 5% of workers filed more than one declaration.[2] The analysis presented here is restricted to labor income.

The database contains records for all formally employed individuals who paid taxes to the Ministry of Finance in a given year. From these records, one can recover gender, age, place of residence, and a comprehensive income measure that covers wages, bonuses, and additional payments, such as severance. Other forms of income, such as rents or capital gains are not included in this database. An important limitation is that one cannot identify employers.[3]

Some population groups are excluded from the tax data. Most ordinary agricultural income falls outside PIT: farmers' social insurance is administered by KRUS (the Agricultural Social Insurance Fund), while special branches of agricultural production may be taxed under PIT. Self-employed individuals can choose to pay income tax or corporate tax; business-income declarations under income tax exist in the Ministry of Finance database, but GRID excludes self-employment income from the labor-earnings sample for cross-country comparability, and self-reported business revenue is in any case a less reliable measure of earnings, as it may be manipulated.

In each year, individuals can be dropped from the sample for various reasons. First, individuals might not receive any labor income in a particular year, for example due to long-term unemployment or prolonged leaves. Second, a worker who moves entirely into self-employment or agricultural work leaves our labor-earnings panel, since the GRID earnings measure excludes self-employment and agricultural income. Third, the database does not track individuals as they move abroad. Finally, it does not contain information on individuals who are retired or collect different pensions (e.g. disability).

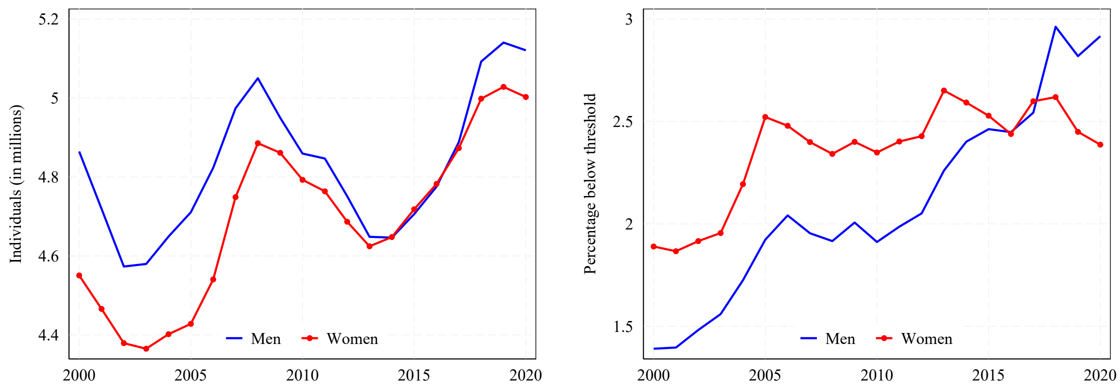
The database comprises around ten million individuals aged 25 to 55 in each year, as shown in Panel (a) of Figure 2. The number of men is slightly higher than the number of women (up to 51% of individuals). Following GRID guidelines, we exclude individuals whose yearly income falls short of three months of half-time employment at the minimum wage, equivalent to 1.5 times the monthly minimum wage. Between 1.5% and 3% of individuals reported earnings below this threshold. This proportion increased throughout the sample, which probably reflects the increase in minimum wages observed during that period. An analysis across age groups reveals a clear life-cycle pattern, see Figure A1 in Appendix A. The proportion below the threshold is higher among young workers, who are entering the labor

[2]The value comes from internal reports (Chrostek et al. 2019, 2022). The statistic is based on all tax forms, and not the subsample used in GRID.

[3]Social security records contain information on employers, such as industry or size. However, it is only possible to match individuals as of 2015.

market, and among workers older than fifty years, where it might reflect a transition to early retirement. Among older workers, the proportion below the threshold is higher for women than for men.

Figure 2: Characterization of PIT database



(a) All observations

(b) Percentage excluded based on income

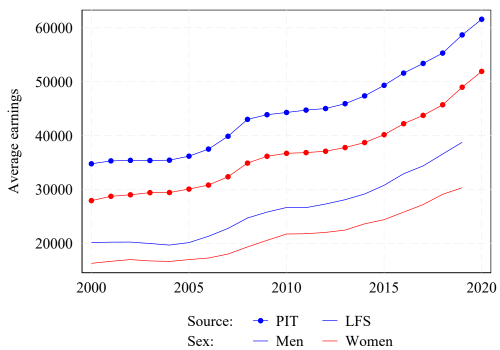
Notes: The sample comprises individuals aged 25 to 55 years old who have paid taxes in the year. Figure on the left shows the total number, by gender. Figure on the right shows the percentage of observations that each year recorded yearly earnings below 1.5 times the minimum wage.

Earnings information on the tax data can be compared to two regular surveys run in Poland: the Structure of Earnings Survey and the Labor Force Survey. The first database is collected from firms every second year. It provides precise information on wages and their components, and on hours worked. This database contains larger samples, between 600 thousand and 800 thousand individuals. However, agriculture and small businesses are not well represented in this database. The Labor Force Survey is collected directly from workers every quarter. It has a better coverage across sectors, but income reporting is more selective and subject to misreporting. As a result, effective sample sizes are smaller, around 7 to 10 thousand individuals.

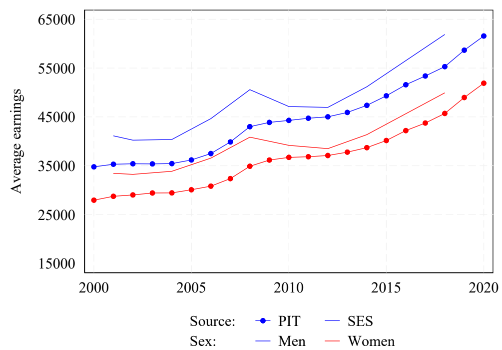
The two panels displayed in Figure 3 compare the average earnings across databases. In these figures, series drawn with markers represent data from tax records, and series drawn without markers values from the alternative samples. As in previous figures, we distinguish between male and female earners. We implement the same sample restrictions as in GRID: we only keep observations between 25 and 55 years old, who earn sufficiently high wages. Given that the sample is monthly, we multiply income by twelve before imposing this criterion. We also exclude self-employed individuals and farmers.

Two messages emerge from these figures. First, earnings in tax income data follow the same time patterns as in SES and LFS. Second, average wages from PIT data are in between values from these two databases. These differences can reflect sampling criteria. It has long been recognized that surveys fail to track incomes at the top of the distribution; this might explain why averages in LFS are below those in tax data. On the other hand, average earnings in the SES can be higher if selected firms are not representative of the overall economy, or workers are not selected entirely at random.

Figure 3: Earnings across different databases



(a) Comparison to Labor Force Survey



(b) Comparison to Structure of Earnings Survey

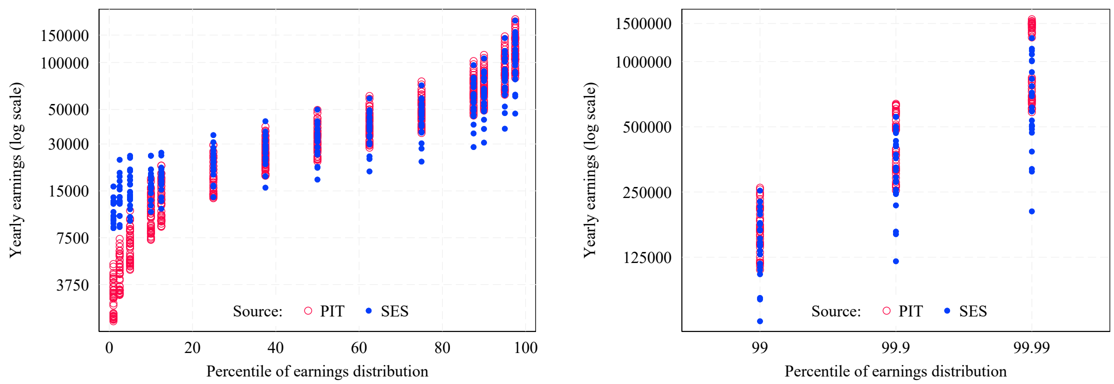
Notes: Figure compares average earnings from tax data to two alternative databases: Labor Force Survey (LFS) and the Structure of Earnings Survey (SES). The sample includes individuals aged 25 to 55 whose annualized income exceeded 1.5 times the monthly minimum wage.

Figure 4 expands the comparison between PIT and SES data to other percentiles of the distribution. Wages in SES are more compressed than tax data at both ends of the distribution. At the bottom, wages in SES are larger, which is expected given that the annualization of wages does not impute any period of unemployment. At the top 1% and higher, percentiles obtained from SES are lower than those computed using PIT data. The difference increases as we move towards the higher percentiles of the distribution. For most of the distribution, between the 20th and 80th percentile, the overlap between databases is substantial.

4 Income dynamics in Poland

In this section, we present statistics on earnings dynamics in the Polish tax data, separately for women and men. We first document the evolution of cross-sectional inequality over 2000–2020, distinguishing the pre-pandemic trend through 2019 from the final COVID year when relevant. We then characterize the distributional properties of earnings growth by examining the dispersion and higher-order moments of 1-year earnings changes. Finally, we analyze income mobility over the life cycle and across the distribution by tracking individuals over time.

Figure 4: Percentiles of earnings across different databases



(a) Main percentiles

(b) Top percentiles

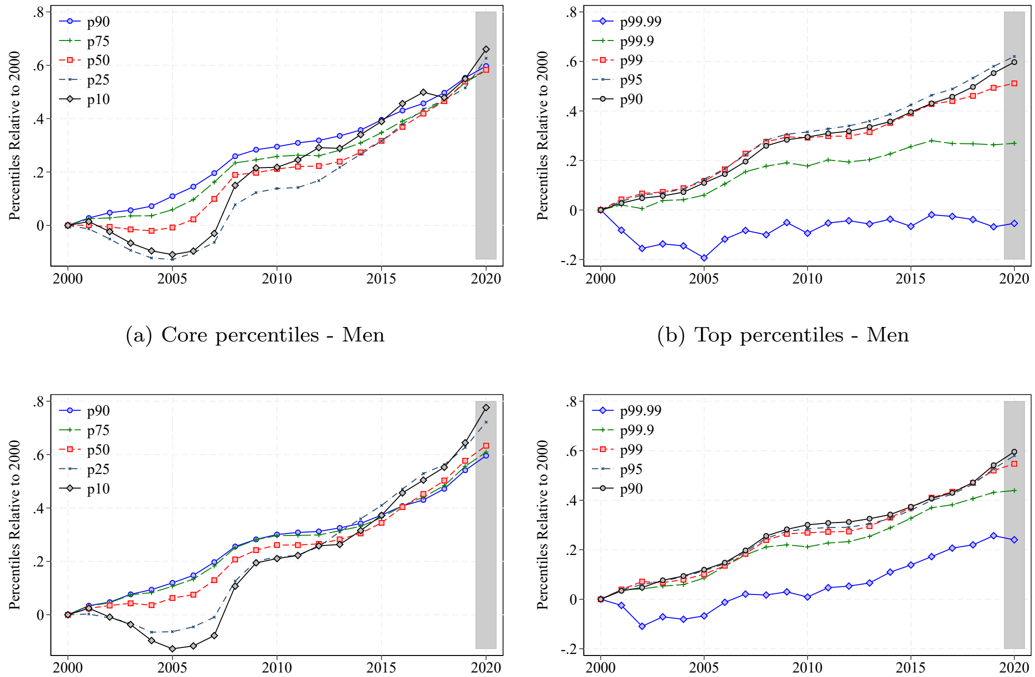
Notes: Figure compares percentiles of earnings distribution computed from PIT and SES data. Each dot represents a percentile for a given year for each gender. Only individuals aged 25-55 whose annualized earnings are above 1.5 times the monthly minimum wage are included. Figure on the right zooms in the top one percent.

4.1 Inequality

Figure 5 shows that there has been substantial real earnings growth across all segments of the distribution. Since 2000, nearly all displayed percentiles have increased, with earnings at the bottom of the distribution growing disproportionately more than those at the top; the male top 0.01% is the exception, as discussed below. For example, earnings at the 90th percentile rose by about 60 log points for both men and women, while the 10th percentile rose by 65 log points for men and 80 for women. This narrowing of the earnings distribution has not been uniform throughout the twenty-year period. Figure 5 suggests two subperiods. Between 2000 and 2005, lower percentiles declined markedly – by 2005 the 10th percentile was around 11 log points below the initial year, while the 25th percentile was around 7 log points below. As of 2006, and particularly as of 2007, these percentiles began to grow faster.

Two contemporaneous developments provide possible interpretations of this pattern. On the one hand, and as shown in the previous section, unemployment rate began to decline at around the same time. As fewer people worked part-year, the lower percentiles would mechanically increase. Panel (a) of Figure 2 provides indirect support for this interpretation: during the first three years, the sample size decreased and later quickly rebounded. This pattern suggests an increase in inactivity during these years. A second element to consider are minimum wages. Between 2007 and 2009, real minimum wage increased by 25%. The equalizing role of minimum wages in Poland has been highlighted by Albinowski and

Figure 5: Change of Percentiles of the log real earnings distribution – by gender



(a) Core percentiles - Men

(b) Top percentiles - Men

(c) Core percentiles - Women

(d) Top percentiles -Women

Notes: Percentiles relative to 2000. Panels (a) and (c) show core percentiles (P10, P25, P50, P75, P90). Panels (b) and (d) show top percentiles (P90, P95, P99, P99.9, P99.99).

Lewandowski (2021), and it matches the findings obtained by Engbom and Moser (2022) for Brazil.

Descriptive evidence on the relation between minimum wages and the evolution of lower percentiles is presented in Figure A2 in Appendix A. This figure displays the ratio of several percentiles of the income distribution to the minimum wage. Across percentiles, we observe two different trends. Up to 2006, lower percentiles declined as a proportion of the minimum wage, while the middle and upper ratios were more stable. As of 2006, the trend is reversed. Lower percentiles grew at a similar rate as the minimum wage. In fact, the ratio hovers at around one for the 25^{th} percentile. By contrast, at the upper percentiles the ratio declined. We return to this analysis in Section 5.

An alternative explanation for the behavior of the lower percentiles is related to migration patterns. As discussed in the previous section, the period 2004-2008 witnessed the largest outflow in Polish history. Two mechanisms can operate. If migrants are from high unemployment regions, then their emigration can reduce the proportion of people employed part-year, which would mechanically raise the lower percentiles. However, evidence presented in

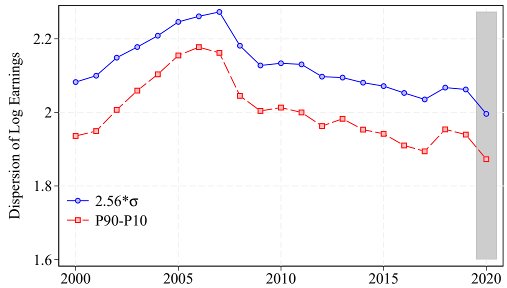
Kaczmarczyk and Okolski (2008) shows that migrants were not more likely to come from regions with high unemployment levels. The second mechanism refers to reservation wages. Migrants can support families through remittances, which could increase reservation wages or facilitate transitions to inactivity. The regional evidence therefore weighs against the first mechanism, while the second we cannot test: the tax records identify neither emigrants nor remittance income.

To some extent, this link might be specific to Poland. First, it is a country with a sufficiently large formal sector. If informality prevails, minimum wage increases might not translate to workers' income. Second, in Poland changes in minimum wages had muted effects on employment levels (Kamińska and Lewandowski 2015). Had employment declined in response to minimum wage changes, the lower percentiles of annual earnings could fall as well, as people would work only part of the year. Finally, and taking into account that workers earning minimum wage were more likely to receive envelope wages, we cannot rule out that part of the growth at lower percentiles is due to changes from envelope to regular wages. This would be consistent with evidence on firms reducing non-cash (or undeclared cash) component of earnings in response to minimum wage increases discussed in Clemens (2021).

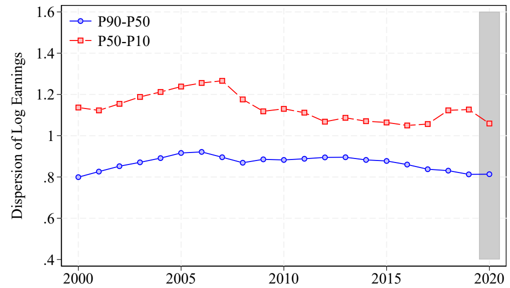
Panels (b) and (d) of Figure 5 show the upper part of the earnings distribution. The dynamics of top percentiles show a similar increase in their values, with the exception of the top 0.01%, which was approximately flat or slightly below its 2000 level for men and increased by slightly more than 20 log points for women. One possible explanation refers to the tax system, as high earners might switch to Business-to-Business contracts more often. Under these arrangements, workers act as self-employed contractors instead of employees, and their incomes are not captured in the database (see Brzezinski et al. 2022). Klejdysz and Zawisza (2026) provide support for this thesis. They find that the introduction of a flat tax rate for business income lead to an increase in self-employment among earners in the top 2 percent. The effect might intensify as one moves further up in the income distribution.

Figure 6 presents the evolution of earnings inequality. Panels (a) and (c) show overall dispersion as measured by the P90-P10 percentile difference and the standard deviation of log annual earnings. For both men and women, inequality initially increased, peaking around 2006, before declining steadily through 2019. Among men, the P90-P10 log-earnings gap fell from around 2.17 in 2006 to below 1.93 by the pre-pandemic endpoint, roughly a 10.9% decline in the log gap itself; because P90-P10 is a difference in logs, this corresponds to an approximately 21% decline in the underlying P90/P10 earnings ratio. Among women, the pattern is similar but more pronounced: inequality rose sharply in the early 2000s before

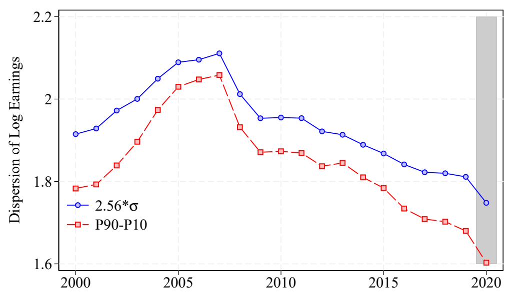
Figure 6: Earnings inequality, by gender



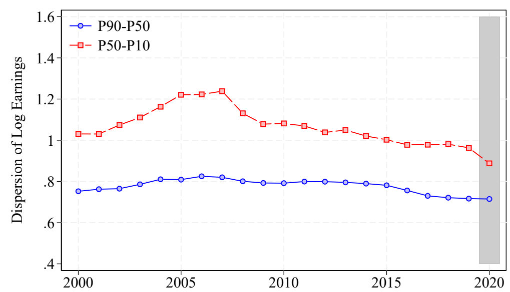
(a) Dispersion – Men



(b) Bottom and top dispersion – Men



(c) Dispersion – Women



(d) Bottom and top dispersion – Women

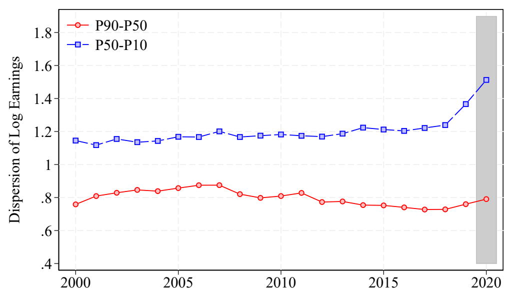
Notes: σ denotes the standard deviation of log real annual earnings. Panels (a) and (c) show overall dispersion measured by P90-P10 and standard deviation. Panels (b) and (d) show bottom (P50-P10) and top (P90-P50) tail inequality.

declining after 2006. The net result for women is a decline in earnings inequality during the two decades under study. Like in most countries of the first phase, the percentile measure of dispersion falls below the parametric value implied by a log-normal wage distribution.

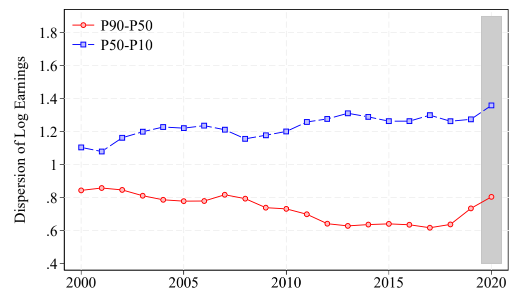
Panels (b) and (d) decompose overall inequality into bottom-tail (P50-P10) and top-tail (P90-P50) dispersion. For men, bottom-tail inequality was initially higher and more volatile, declining substantially after 2006, while top-tail inequality remained relatively stable around 0.8. For women, a similar pattern emerges: the P50-P10 differential peaked around 2006 at over 1.2 before falling to around 1.0, while the P90-P50 differential declined more gradually from 0.9 to below 0.7. The sharper decline in bottom-tail inequality is consistent with the faster growth of the lowest percentiles after 2006 documented above. The Gini coefficient, shown in Figure C4 in Appendix C, confirms these patterns: it peaked around 2006 and has declined since, for both men and women.

Our findings reproduce the trends in wage dispersion documented by Magda et al. (2021) using data from the Structure of Earnings Survey. This initial increase and further decline is common to most Central and Eastern European countries. They decompose inequalities and show that the between-firm component of variance decreased more than the within component showing an equalization of average wages across firms, though not as pronounced as in other countries.[4] Using a quantile decomposition, Magda et al. (2021) also show that the compression was driven by wage structure effects (return to characteristics). Changes in the composition of workers alone would have led to an increase in wage dispersion. Wage structure effects were more important at the bottom of the distribution, particularly in countries where minimum wage exhibited stronger growth, such as Poland. [5]

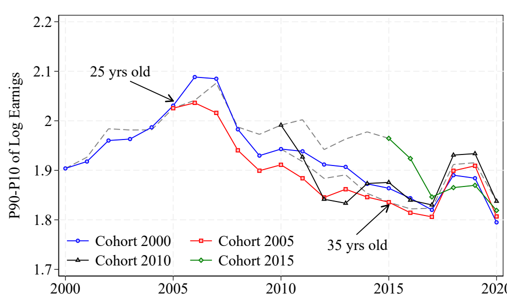
Figure 7: Inequality and age profiles for young workers, by gender



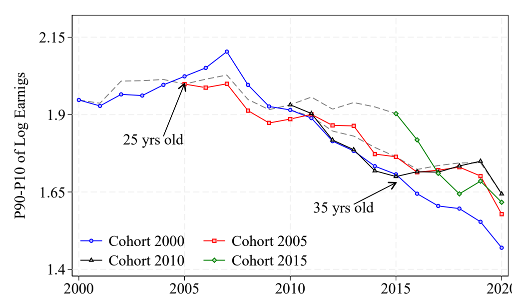
(a) Income dispersion at age 25 – Men



(b) Income dispersion at age 25 – Women



(c) Life-cycle inequality over cohorts – Men



(d) Life-cycle inequality over cohorts – Women

Notes: Panels (a) and (b) consider only workers aged 25. Panels (c) and (d) plot earnings inequality profiles by cohorts and age groups.

Figure 7 examines initial earnings inequality and its evolution over the life cycle. Panels (a) and (b) show the dispersion of earnings among labor market entrants, at age 25, decomposed into bottom-tail (P50-P10) and top-tail (P90-P50) inequality. For both men and women, initial inequality is substantially higher at the bottom of the distribution than at the top.

[4] Alvarez et al. (2018) find a strong decline in the between-firm component in reaction to minimum wages. Song et al. (2019) also show that the changes to the between-firm component drive recent trends in wage inequality in the United States.

[5] Our analysis focuses exclusively on labor earnings and does not capture, for example, business income which Brzezinski et al. (2022) show has become increasingly important for top earners in Poland.

Among men, bottom-tail inequality (P50-P10) remained relatively stable around 1.1-1.2 until 2018 then increased sharply to around 1.5 by 2020, possibly as a result of declining wages at the bottom of the distribution. Among men, top-tail inequality (P90-P50) was stable at around 0.8 throughout the period, and similar to that among the population as a whole. Among women, the period after 2008 was marked by an increase in the P50, which compressed top-tail inequality and widened bottom-tail inequality. The uptick in the final year coincides with both the introduction of a tax break for workers under 26 years old and the subsequent pandemic, though we cannot separately identify the contribution of each factor here.

Panels (c) and (d) track life-cycle inequality profiles across different cohorts. For men, all cohorts exhibit a similar pattern: inequality (measured by P90-P10) starts high around age 25, at approximately 2.0-2.1, and then declines as workers age. By age 35, inequality falls to around 1.8-1.9. Earlier cohorts (2000, 2005) entered the labor market with higher initial inequality than later cohorts (2010, 2015). Women exhibit a similar pattern, where high inequality in the early sample years is followed by a compression of the income distribution. Women's earnings ultimately become more compressed. The decline in aggregate inequality observed in Figure 6 reflects both changes in initial conditions, with more recent cohorts entering with lower dispersion, and compression within cohorts as workers age. The raw cohort profiles decline with age, but because all cohorts traverse the same period of aggregate compression, Figure 7 alone cannot distinguish an age profile of inequality, such as the profiles observed for men in Germany (Drechsel-Grau et al. 2022) and to some extent in France (Kramarz et al. 2022), from calendar-time effects; the evolution of inequality within cohorts appears to be driven primarily by the overall evolution of wage dispersion in the economy.

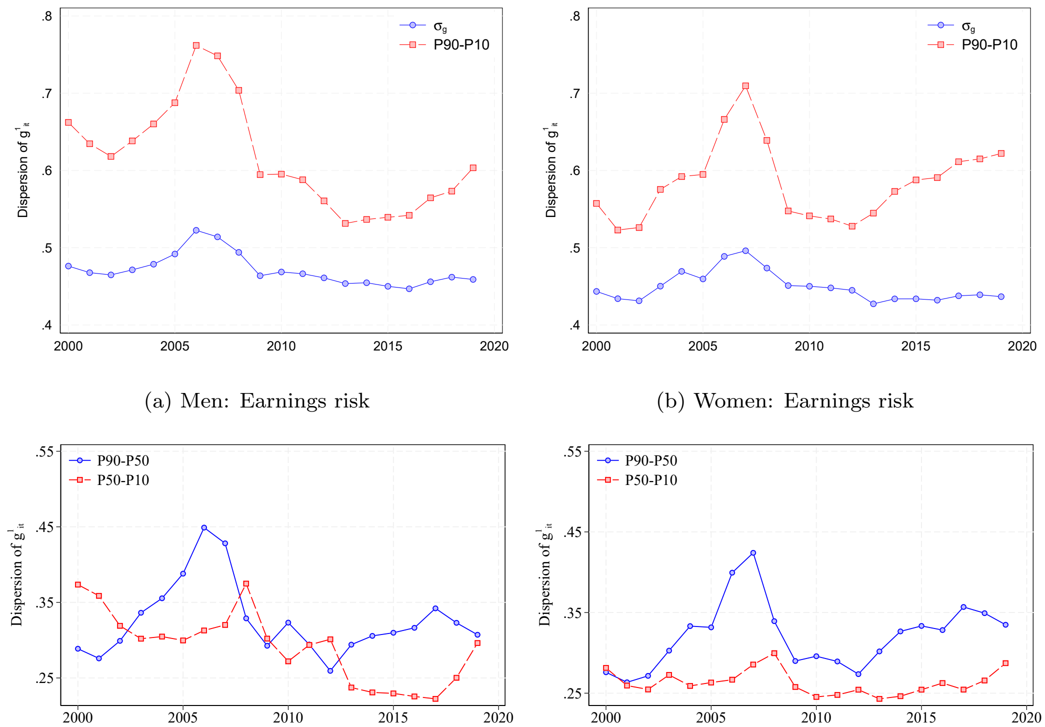
Additional inequality statistics for the pooled sample, including changes in income shares (Figure C3) and Gini coefficients, are presented in Appendix C. The pooled sample exhibits similar patterns to the gender-specific results, as shown in Figures C1 and C2.

4.2 Income Dynamics

This section describes the evolution of residualized earnings changes. Following the GRID template, in each year we regress log labor income on a full set of age and gender dummies and retain the residuals, which we interpret as "residualized earnings." We then compute individual-level changes in these residuals across periods to characterize the distribution of earnings dynamics. These differences are forward looking, i.e., $g^1_{it} = e_{i,t+1} - e_{i,t}$.

Figure 8 shows the dispersion of year-to-year changes in residualized earnings, a measure commonly used as a proxy for idiosyncratic earnings risk. The standard deviation of annual

Figure 8: Dispersion of 1-year log earnings changes, by gender



(a) Men: Earnings risk

(b) Women: Earnings risk

(c) Men: upper and lower dispersion

(d) Women: upper and lower dispersion

Notes: 1-year changes in residualized log earnings.

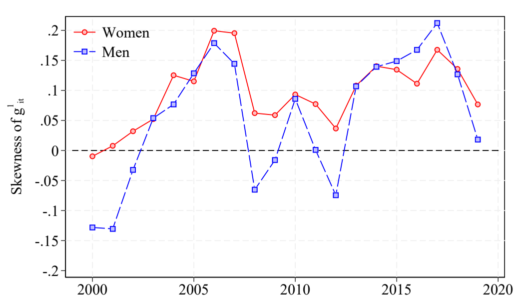
residualized log-earnings changes is approximately 0.45-0.55 for both genders, indicating substantial dispersion. The standard deviation shows remarkable stability over the twenty years for which we have data, with only a small hump in the period between EU accession and the global financial crisis. Using this measure, men display slightly higher dispersion than women throughout most of the period. However, since 2012 the difference in percentiles is higher for women than for men. The dispersion tends to converge towards the end of the sample.

This gap may partly reflect sectoral composition, as women are overrepresented in the public sector (Goraus and Tyrowicz 2014), where earnings tend to be more stable (see Gomes and Kuehn 2026, for a broader context). Moreover, men tend to be more represented among workers in larger firms, which can afford larger bonuses. Figure A3 in the Appendix documents this composition directly using LFS data: women's share among public-sector workers rose from roughly 52% in 2000 to over 60% by the end of the sample, while for the sample period the share of women in large firms remained below 45%. Figure A3 also shows that women are overrepresented among individuals with tertiary education, while remaining slightly less than half of all employed workers.

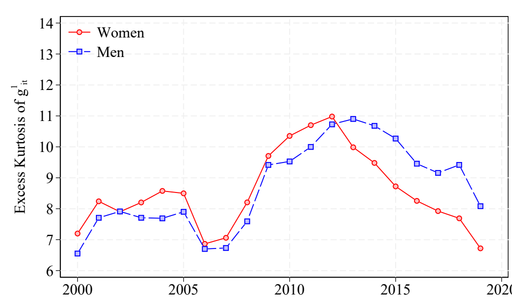
While men and women converged to a similar overall dispersion of earnings changes, Panels (c) and (d) show that the shape of this dispersion differed by gender. Among women, lower tail inequality remains almost constant at low values. Its values lie between those reported for France (0.4) and the United Kingdom (0.2) (Kramarz et al. 2022, Bell et al. 2022). The hump-shaped pattern observed in Panel (b) is driven by fluctuations in the dispersion of positive changes. Among men, the lower tail of the distribution of changes became more compressed over time until recent years. We observe lower-tail spikes in 2008 and 2012, matching the years of the financial and Euro crises.

In the first half of the sample, the distribution of earnings changes followed a similar pattern to wage inequality. The spread of earnings changes increased during the years after EU accession, and it was driven by an expansion of the upper tail. The interpretation is intuitive: during expansions, large positive earnings changes (promotions, bonuses) become more common. However, after 2008 we observe a decline in earnings inequality that is not matched by a similar reduction in the spread of earnings changes. While the earnings distribution compressed substantially between 2008 and 2019, the year-to-year volatility faced by individual workers changed little or even increased.

Figure 9: Higher moments of 1-year log earnings changes, by gender



(a) Kelley Skewness



(b) Excess Crow-Siddiqui Kurtosis

Notes: 1-year changes in residualized log earnings.

We now characterize higher-order moments of earnings changes to assess deviations from log-normality. Panel (a) of Figure 9 shows the Kelley skewness of 1-year earnings changes. The most striking feature is the pronounced cyclicality. For men, skewness started negative (around −0.13) in 2000–2002, rose sharply to peak near 0.18 during the post-EU accession boom (2006–2007), and turned negative again in weaker labor-market periods around 2008–2009 and 2012. The index recovered strongly toward the end of the sample, before declining in 2019. Women exhibit a similar cyclical pattern, but skewness is generally positive and much less often negative.

Panel (b) shows the excess Crow-Siddiqui kurtosis. The persistently high values indicate that the distribution of earnings changes is far from normal: in any given year, most workers experience modest changes while a minority experience very large swings. This leptokurtic pattern is common across countries in the GRID project, though the values for Poland, approximately 6.5 to 11, are lower than among developed European countries. Kurtosis also varies cyclically, but in a different manner than skewness: it reached a minimum around 2006, when skewness peaked, and a maximum in 2012–2015, when skewness was low.

While skewness follows a similar cyclical pattern across the two expansionary periods (2006–2007 and 2015–2019), robust kurtosis is higher during the second expansion. Because Crow-Siddiqui kurtosis is the ratio of the outer-percentile spread (P97.5-P2.5) to the interquartile range (P75-P25), its level depends on the relative behavior of both components, and we do not attempt to attribute the difference across the two expansions to a single mechanism here. Analogous patterns for 5-year earnings changes are presented in Appendix D (Figures D1, D2, and D3).

After 2012, Crow-Siddiqui kurtosis declines for women, but less so for men. The gender patterns are informative. During the initial period, income changes for women exhibited somewhat higher kurtosis, whereas the positions are reversed after 2012. A detailed look at the percentiles shows that in each year after 2013, the spread between p75 and p25 was larger among women than among men. Moreover, it grew faster over the same period: this spread grew around 33% for women, but only 26% among men. By contrast, the numerator (P97.5-P2.5) was fairly stable over the same period for men and women alike. Because kurtosis is the ratio of these two ranges, a stable numerator combined with a faster-growing denominator mechanically lowers the statistic, consistent with the sharper post-2012 decline in kurtosis among women. This widening of the interquartile range could reflect family formation patterns: women are more likely to reduce labor market participation after childbearing (Cukrowska-Torzewska and Lovasz 2016), and these interruptions create two changes in our data, at exit and at entry, which can increase the dispersion of earnings changes around the center of the distribution while leaving the tails less affected. This greater dispersion of changes among women was already visible in Figure 8.

Figure 10 examines how earnings risk varies across the permanent income distribution and age groups. For comparison, the values averaged over years of the P90-P10 differential for the entire population stood at 0.58 for women, and 0.61 for men. Panels (a) and (b) show the dispersion of 1-year earnings changes (P90-P10 differential). For both men and women, dispersion is highest at the bottom of the permanent income distribution, reaching values above 1 for the lowest decile, and declines sharply as permanent income increases. By the 20th percentile, the slope is less steep, but still negative. It is only among the higher percentiles, P90 and above, that dispersion increases again. The increment among higher earners is particularly noticeable among men.

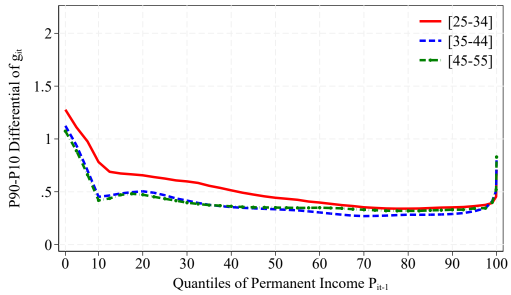
Men and women experience different earnings risk as they age. Among men, younger workers (25-34) exhibit a slightly higher dispersion at the bottom of the permanent income distribution. However, by the 50th percentile the gap to older age groups is already closed. Among women, age differences are more pronounced: young women exhibit substantially higher earnings risk across the entire distribution compared with older age groups. This pattern was documented in other countries as well (Kramarz et al. 2022, Drechsel-Grau et al. 2022, Hoffmann et al. 2022, Leth-Petersen and Sæverud 2022)

Panels (c) and (d) display Kelley skewness across the permanent income distribution. For men, skewness is positive at the bottom of the distribution (around 0.2 for the lowest decile), indicating that upward earnings movements are more common than downward ones among low earners. Skewness declines toward zero as permanent income increases, becoming slightly negative for workers above the median. The pattern is similar across age groups. A possible explanation relates to the role of minimum wages. In a tight labor market, minimum wage hikes compress the left tail of earnings changes among low earners, producing positive skewness. To the extent that spillover effects raise wages further up the distribution by varying amounts, they may also widen the overall spread of changes above the minimum wage threshold. Among women, the profile is qualitatively similar but with notable age heterogeneity: young women (25-34) show positive skewness at the bottom that turns negative around the median, suggesting that higher-earning young women face a greater incidence of negative earnings changes, potentially reflecting employment interruptions due to childbearing, as women with higher earnings can potentially afford longer leaves.

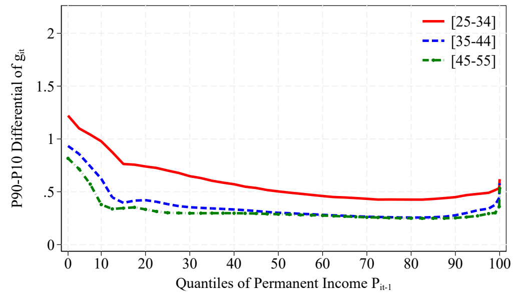
Panels (e) and (f) present excess Crow-Siddiqui kurtosis. For both genders, kurtosis is larger at the bottom of the permanent income distribution, exceeding 15 for workers older than 35 years old: the outer-percentile spread is large relative to the interquartile range, well beyond what a normal distribution would predict. Kurtosis declines rapidly with permanent income, stabilizing around 3-5 between the 20th and 80th percentiles. Young workers have lower kurtosis than older workers at the bottom of the permanent-income distribution, but this ranking reverses from around the 20th percentile onward. At the top of the distribution, kurtosis rises again, particularly for older workers aged 45-55. The high kurtosis, especially below the 30th percentile, is consistent with non-Gaussian income dynamics reported in other countries.

These patterns reveal substantial heterogeneity in earnings risk. Young workers have higher dispersion of earnings changes, while age differences in robust kurtosis reverse across the

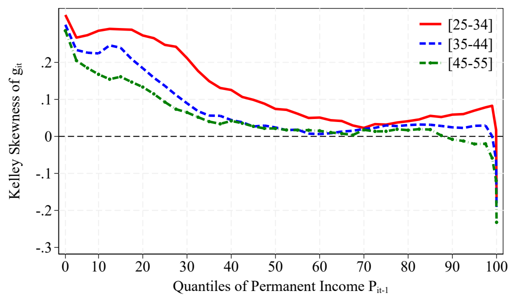
Figure 10: Dispersion, Skewness, and Kurtosis of 1-year log earnings changes by gender, age, and permanent income quantiles



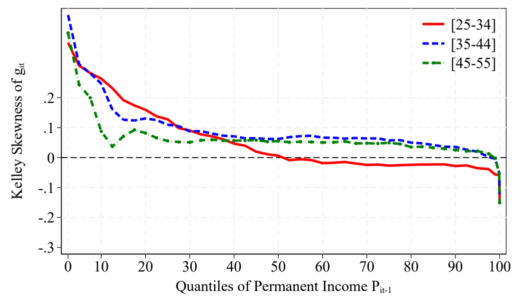
(a) Dispersion – Men



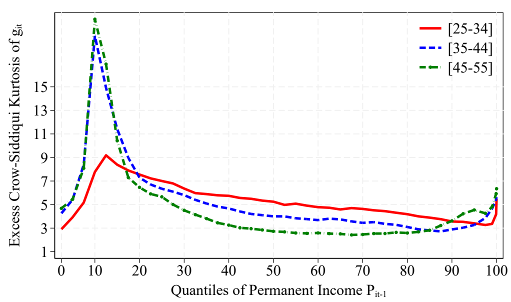
(b) Dispersion – Women



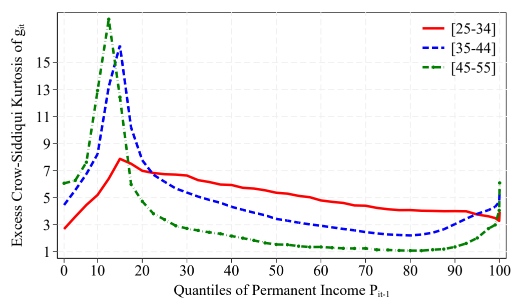
(c) Kelley Skewness – Men



(d) Kelley Skewness – Women



(e) Excess Crow-Siddiqui Kurtosis – Men



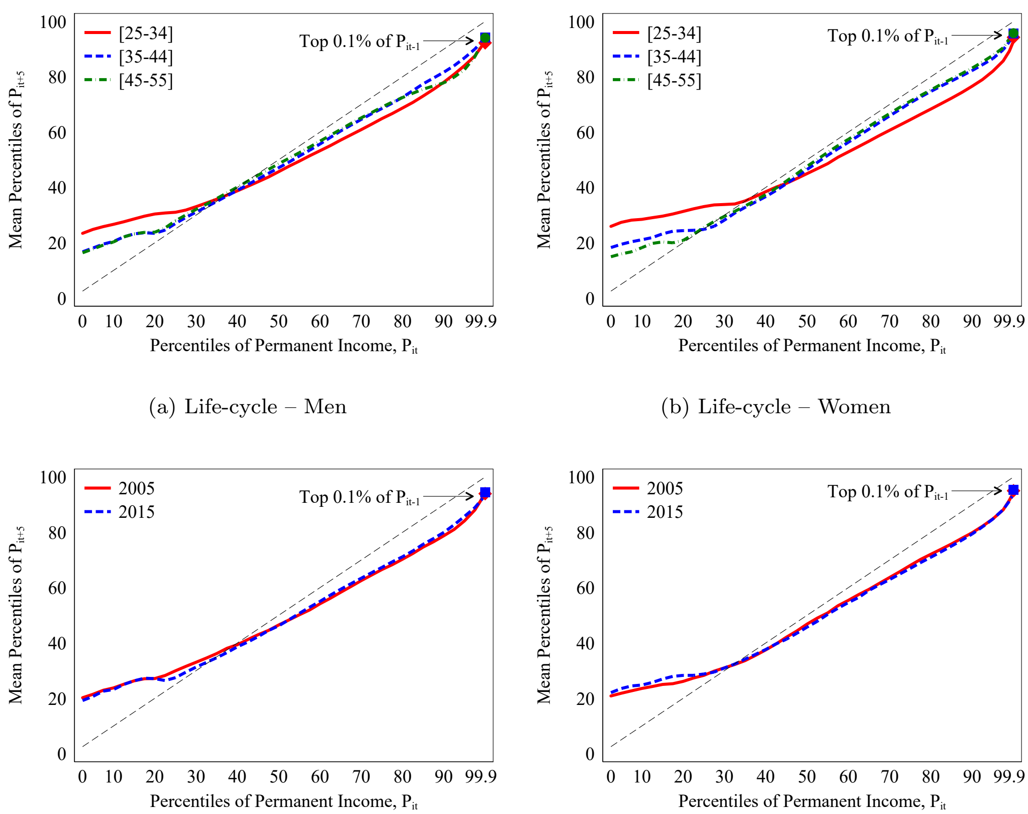
(f) Excess Crow-Siddiqui Kurtosis – Women

Notes: 1-year changes in residualized log earnings by permanent income quantiles. Permanent income is defined as the average earnings over the previous 3 years. Lines correspond to different age groups: 25-34, 35-44, and 45-55.

permanent-income distribution. The positive skewness at the bottom of the permanent-income distribution reflects a greater incidence of large positive earnings changes relative to large negative ones among low earners; the elevated kurtosis indicates that outer-percentile earnings changes are large relative to the interquartile range, though this does not by itself establish how often such changes occur. The distinctive profile of young women, with higher dispersion and negative skewness in the upper half of the permanent-income distribution, could be consistent with, among other mechanisms, labor market interruptions associated with family formation. Empirical densities of 1-year and 5-year earnings growth, shown in Figures D4 and D5 in Appendix D, illustrate the non-Gaussian shape of the earnings change distribution, with pronounced peaks near zero and heavy tails.

4.3 Mobility

Figure 11: Evolution of 5-year income mobility



(a) Life-cycle – Men

(b) Life-cycle – Women

(c) Over time – Men

(d) Over time – Women

Notes: 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 and averaging across all age groups. The black diagonal dashed line is the 45-degree line that corresponds to the case of no mobility.

Figure 11 presents 5-year mobility statistics. These figures plot the current permanent-income rank against mean rank five years later. Values close to the 45-degree line indicate no mobility, whereas a horizontal line would indicate complete mobility, i.e. the current position does not predict future values. Values above the 45-degree line indicate that average rank increases over time, whereas values below indicate a decline in average rank. The main story that emerges from this picture is one of substantial upward mobility up to the 30th-40th percentile, and downward mobility thereafter. This S-shaped rank-rank curve—upward mobility at the bottom followed by downward mobility at the top—reflects a combination of low overall mobility and mean reversion. The degree of mobility falls below what is observed in more egalitarian countries, such as Norway or Denmark (Halvorsen et al. 2022, Leth-Petersen and Sæverud 2022).

Figure 11 explores differences by age groups and over time. Panels (a) and (b) present mobility of men and women from a life-cycle perspective. For both genders, the curves reveal substantial mobility among the youth, and more stable positions as individuals age. Both patterns are more pronounced among women. Young women exhibit greater upward mobility, both in size of the jump (difference between percentiles at t and $t+5$), and in the proportion, as the mobility curve intersects the axes at a higher level. Women older than 35 display greater income stability than men, particularly at the top of the income distribution.

This higher mobility among the youth is a common finding across papers in the GRID project. This pattern suggests that earnings today are worse predictors of future earnings when an individual is young, which is consistent with models of employer learning, where earnings exhibit increasing correlation with individual productivity (Jovanovic 1979, Farber and Gibbons 1996), which implies more stable rankings.

The greater downward mobility of young high-earning women could be consistent with, among other mechanisms, the child penalty (Kleven et al. 2019): women near the top of the earnings distribution at a young age may be more likely to take extended leave around childbirth, which could produce large downward rank movements. We do not observe births directly and so cannot test this mechanism; we note only that this pattern is not visible for women older than 35 years old, who have typically completed family formation, and that it is also consistent with the higher variation of income growth documented in the previous section. Our rank-based statistics should not be read as evidence on the long-run earnings cost of motherhood. Kleven et al. (2025) estimate a 32.2% child penalty in employment in Poland, the average effect of parenthood on women's employment relative to men's over a decade following the first birth, scaled by counterfactual employment absent children. This effect on employment makes scarring difficult to detect in our data, because exits from employment, the margin on which much of the penalty operates, remove women from the sample. The temporary downward rank movements of young high-earning women documented above are therefore complementary to, not a substitute for, event-study evidence on child penalties.

Panels (c) and (d) show that the patterns described earlier were stable over time. The years selected show mobility in the aftermath of EU accession, where unemployment rate was high, and minimum wages were low; and, in the last years of our sample, when unemployment had receded and minimum wages were higher. In spite of these differences in context, the lines mostly overlap. Among women, one may notice an increase in mobility at the bottom of the permanent income distribution. This overlap is another common feature among GRID countries. Mobility appears to be shaped more by slow moving institutional characteristics than by business cycle considerations.

5 Earnings dynamics and macroeconomic conditions in Poland

[6] In the previous sections, we reviewed macroeconomic trends in Poland and emphasized the role of three elements: rapid economic growth, large fluctuations in unemployment, and large increases in the minimum wage. Read alongside Section 4, they pose a puzzle: Poland's macroeconomic environment is unusual among GRID countries, while most of the earnings statistics we document are in line with evidence from other countries. This section asks which parts of the earnings distribution moved with these distinctive aggregate forces, and which did not.

We apply percentile-level regressions, a quantile-beta analysis run on the harmonized GRID statistics, as in, for example, Chang et al. (2026) for Korea, or Floccari and Karpati (2026) for the Netherlands. The results discipline the reading of Section 4: they locate the compression documented there at the bottom of the cross-sectional distribution, where the minimum wage binds; they show that increases in unemployment shift the whole distribution of individual earnings changes to the left; and they show that the higher moments of earnings changes move largely independently of these aggregate series.

5.1 Income inequality

As shown in the previous section, income inequality in Poland followed an inverse-U shape trajectory. During the first years, inequality rose as lower percentiles declined. The recovery, which started as early as 2005, closed the gap between percentiles and eventually led to a decline in inequality. We alluded to two possible factors that contributed to this narrowing of the income distribution: minimum wages, and the decline in unemployment rate. Minimum wages, particularly when binding and enforced, could pull the lower percentiles up (see Albinowski (2018) for evidence from Poland, and Alvarez et al. (2018) for Brazil). On the other hand, the period 2000-2005 was characterized by high levels of unemployment. As

[6] We thank the editor for suggesting this extension to our work

unemployment receded, workers would have shorter periods with no earnings, which again could pull lower percentiles up.

We explore these relationships with the help of auxiliary regressions of the form:

$$\Delta Q_y(p)_t = \beta_0^p + \beta_1^p \Delta \log MW_t + \beta_2^p \Delta U_t + \beta_3^p \Delta \log GDP_t + e_t^p,$$

where the dependent variable denotes changes in the percentiles p of the log-earnings distribution. We use percentiles collected from the entire population. In this regression, we include three right-hand side variables: changes in log minimum wages ($\Delta \log MW_t$), changes in unemployment rate for the entire labor force(ΔU_t), and changes in log GDP ($\Delta \log GDP_t$).[7] Using the statistics distributed by GRID, we estimate this regression for the following percentiles $p \in \{1, 2.5, 5, 10, 12.5, 25, 37.5, 50, 62.5, 75, 87.5, 90, 95, 97.5, 99\}$. The coefficients are estimated using seemingly unrelated regressions, which allow error terms to be related. The estimated coefficients do not represent causal estimates, but rather correlations.

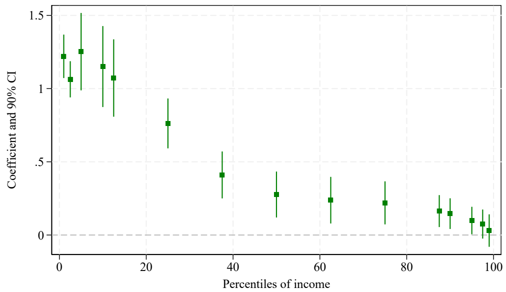
Figure 12 reports the estimates. Table A2 presents additional tests for differences between selected coefficients. In these regressions we observe a strong positive correlation between changes of minimum wages and changes in lower percentiles. A one percent increase in minimum wages is associated with an increase of roughly 0.8 to 1.25 percent in percentiles at or below the 25th percentile. The coefficients gradually shrink as one progresses towards higher percentiles: the estimate at the 95th percentile is only marginally significant, and from the 97.5th percentile onward we cannot rule out that the parameter equals zero. Since coefficients are larger at the bottom end of the distribution, we conclude that increases in minimum wages were related to a compression of the income distribution.

This relation might partly reflect how the sample was constructed. The harmonization process employed at GRID trims observations based on a minimum wage threshold. When minimum wage increases, the selection effect can be stronger. Reassuringly, only between 1.5% and 3% of individuals are excluded from the sample.

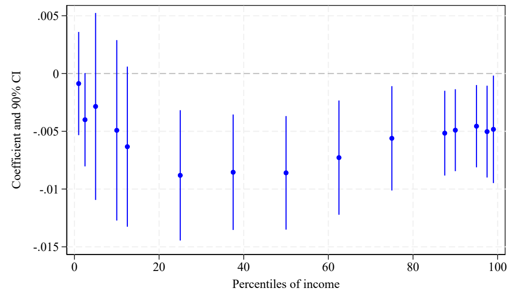
The second variable that we consider is the unemployment rate. Increases in unemployment rate are associated with declines in all percentiles. The coefficients are somewhat more negative in the middle of the distribution, and closer to zero on both ends. We also notice that coefficients are less precise at the lower end of the income distribution. This pattern suggests that periods of high unemployment are associated with a displacement to the left of the income distribution. Because the coefficients at the two ends of the distribution are

[7] Poland has no consistent annual net-migration series covering 2000–2020, which prevents us from including this additional regressor.

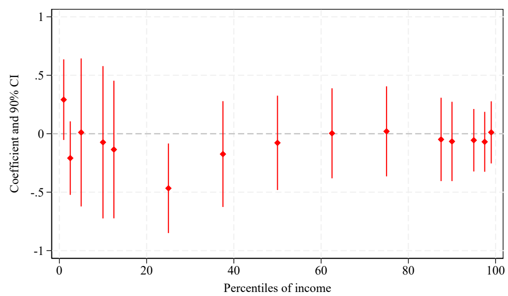
Figure 12: Relationship between macroeconomic indicators and income percentiles



(a) Changes in (log) minimum wages



(b) Changes in unemployment rate



(c) Changes in (log) GDP

Notes: Each panel plots the estimated coefficients across percentiles p of the cross-sectional log-earnings distribution, from the joint seemingly-unrelated-regression system described in the text ($N = 20$ annual observations, 2000–2020). Vertical bars denote 90% confidence intervals.

of similar magnitude, this pattern implies that the lower half of the distribution compresses while the upper half expands by a comparable amount, so that the net implied effect on overall P90-P10 dispersion is close to zero, even though earnings levels decline throughout the distribution when unemployment rises. As we discuss below, this conclusion does not carry over to the specification that considers unemployment alone.

Finally, the relationship between GDP and the income distribution is not precisely estimated, as all confidence intervals are wide. In most cases, these confidence intervals include zero, which prevents us from drawing strong conclusions.

Including these variables in one regression runs into the risk of multicollinearity, which affects the precision of our estimates. Moreover, since changes in minimum wages might reflect changes in GDP, the model might fail to disentangle the two. To address this concern, we estimate a second specification that considers only one variable at a time. These regressions are presented in Table A1 in the Appendix.

These estimates show some differences with respect to those presented in the main text.

First, coefficients on unemployment for lower percentiles still lack precision, but suggest greater declines in percentiles of income than at the higher end: lower percentiles decline more during periods when unemployment is high, and increase more during periods when unemployment is low. Taken together, this specification implies wider P90-P10 dispersion when unemployment rises, in contrast with the approximately neutral effect on P90-P10 implied by the joint specification above. The distributional conclusion is therefore sensitive to which specification is used, even though both specifications associate higher unemployment with a broad decline in earnings levels. Second, while coefficients on GDP are still imprecise, we can observe a split in point estimates. Coefficients below the median tend to be negative, whereas those above tend to be positive. This pattern suggests that periods of faster economic growth were associated with greater income dispersion. However, given the width of confidence intervals, these conclusions should be interpreted cautiously.

Table A1 also includes two additional F-statistics, which evaluate the hypotheses of (a) joint significance of all coefficients related to a given variable, and (b) equality of coefficients across percentiles. In all cases, we soundly reject the null hypotheses. Economic fundamentals are correlated with income percentiles, and these correlations vary across percentiles.

Figure A4 reproduces the analysis separately for men and women. In most cases, confidence intervals for men and women overlap, which prevents us from drawing strong conclusions on gender differences. Only the association between unemployment and inequality appears to be weaker among women, and only for the middle percentiles.

5.2 Income dynamics

Next we explore the relationship between these economic variables and income dynamics. We propose a similar specification

$$Q_{\Delta y}(p)_t = \beta_0^p + \beta_1^p \Delta \log MW_t + \beta_2^p \Delta U_t + \beta_3^p \Delta \log GDP_t + e_t^p$$

where the left hand side describes the distribution of income changes. Concretely, our dependent variables are the percentiles of the distribution of income changes. These are quantiles of annual earnings changes, not changes for workers located at the corresponding quantiles of the earnings-level distribution: a negative coefficient at a low percentile means that the most negative annual changes become more negative, not that low-earning workers as a group lose more. We focus on percentiles $p \in \{1, 2.5, 5, 10, 12.5, 25, 37.5, 50, 62.5, 75, 87.5, 90, 95, 97.5, 99\}$, and estimate the coefficients using seemingly unrelated regressions. The estimated coefficients are presented in Figure 13, and in Table A3 in the Appendix. Table A4 presents additional tests for differences between selected coefficients.

The first panel displays the estimated coefficients for changes in (log) minimum wages across different percentiles of income change. These coefficients have wide confidence intervals, particularly in the lower tail of the distribution. Taken at face value, coefficients indicate that minimum wages are associated with a wider distribution of earnings changes: lower percentiles become more negative, and upper percentiles become more positive. The expansion of the right tail is visible from the 90th percentile onward. This pattern is consistent with, but does not on its own establish, a role for workers whose pay is directly affected by binding minimum-wage increases, since the regression does not identify where these workers were positioned in the prior earnings-level distribution.

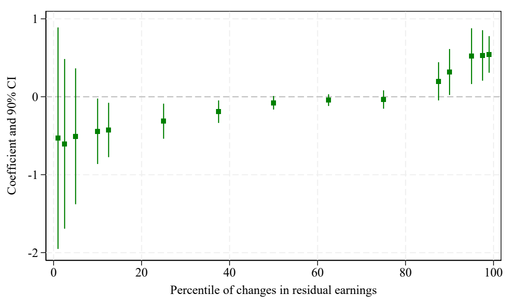
The pattern observed here does not contradict the results presented in the previous subsection. Increases in minimum wages can reduce persistent level differences while increasing year-to-year adjustment around the date of a change. One possible, but untested, explanation is that partial-year exposure to a new minimum wage, together with the large adjustments required to catch up with the new level, widens annual changes for some workers while lower percentiles of the earnings-level distribution catch up over time.

The second panel focuses on changes in the unemployment rate. As with minimum wages, confidence intervals are away from zero at most percentiles, but the pattern across percentiles differs from the minimum-wage gradient described above: coefficients are negative throughout the distribution of earnings changes rather than rising monotonically from negative to positive. An increase in unemployment is associated with smaller residualized income growth at all percentiles, consistent with a higher prevalence of part-year work, and with a broad shift to the left of the distribution of residualized income changes. Because the coefficients are negative throughout rather than symmetric around the center, the implied effect on the overall spread of this distribution is more sensitive to which percentiles are compared than a simple leftward shift would suggest.

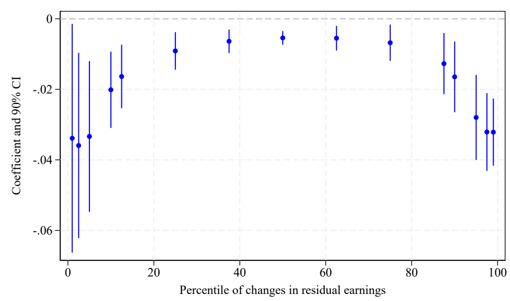
Lastly, the third panel shows the associations between changes in (log) GDP and percentiles of residualized income changes. The pattern differs from the previous variables. The middle percentiles appear uncorrelated with GDP, with point estimates close to zero, and relatively narrow confidence intervals. By contrast, estimates at both tails are larger in absolute values. An increase in GDP is associated with declines in lower percentiles (more negative changes), and increases in the upper percentiles (more positive changes). Taken together, these coefficients suggest greater dispersion of the distribution of annual residualized earnings changes, without a significant change in the center.

Table A3 in the Appendix displays an alternative specification where variables are included

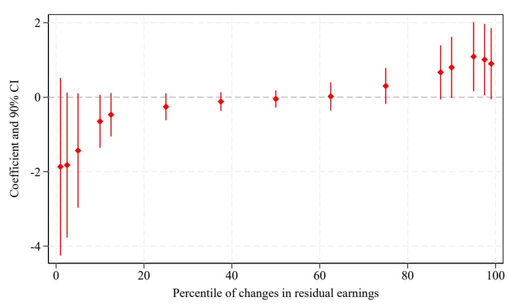
Figure 13: Macroeconomic associations across quantiles of individual one-year earnings changes



(a) Changes in (log) minimum wages



(b) Changes in unemployment rate



(c) Changes in (log) GDP

Notes: Each panel plots the estimated coefficients across percentiles p of the distribution of individual one-year residualized earnings changes, from the joint seemingly-unrelated-regression system described in the text ($N = 20$ annual observations, 2000–2020). Vertical bars denote 90% confidence intervals.

one by one. The sign of the unemployment coefficients is consistent with the joint specification: negative throughout the distribution of earnings changes. However, there are substantial differences in the role of changes in GDP and minimum wages. Coefficients on GDP are larger, and mostly positive. We still observe an increase in the dispersion of earnings changes as GDP increases, but in these regressions the association arises due to larger coefficients in upper percentiles, and not due to changes in sign. The role of minimum wages also differs across specifications. As with GDP, we do not treat the joint and single-variable estimates as interchangeable robustness checks, since they answer different questions—conditional associations that hold the other two macroeconomic variables fixed, versus unconditional associations that do not. The F-statistics presented at the bottom of Table A3 allow rejecting the null hypotheses of joint insignificance, and equality of coefficients.

Figure A5 reproduces the analysis separately for men and women. As in the previous section, we do not find significant differences in association between men and women. The only noteworthy difference concerns the precision of estimates, which is higher among women. The implied shape of the association is similar to that described for the population as a whole.

5.3 Do changes in fundamentals account for the observed patterns?

The coefficients estimated in the previous section can be used to decompose changes in statistics of interest: dispersion, skewness and kurtosis. Consider dispersion of income growth, $D_t := p_{90,t} - p_{10,t}$, first. The growth in dispersion of income growth between a base period b and an end period t can be written as:

$$\frac{D_t}{D_b} = \frac{p_{90,t} - p_{10,t}}{p_{90,b} - p_{10,b}}.$$

Using the results from the previous section, we can decompose the percentiles into a part that is related to changes in economic fundamentals (GDP, unemployment rate and minimum wages), which we denote $\hat{p}_p$ for percentile p, and a residual part that we denote $\hat{e}_p$. These residuals may reflect policy reforms, sector-specific developments, changes in workforce composition or reporting, measurement error, and model misspecification. Given this separation, we can consider a counterfactual exercise, and derive the dispersion in year t had fundamentals remained at base year level. The implied value is $p^c_p := \hat{p}_{p,b} + \hat{e}_{p,t}$. Having defined these counterfactuals we can decompose changes in dispersion into a part that reflects changes in macroeconomic variables, and a part that reflects changes in residuals as follows

$$\frac{D_t}{D_b} = \underbrace{\frac{(\hat{p}_{90,t} - \hat{p}_{10,t}) + (\hat{e}_{90,t} - \hat{e}_{10,t})}{(\hat{p}_{90,b} - \hat{p}_{10,b}) + (\hat{e}_{90,t} - \hat{e}_{10,t})}}_{\text{Changes in fundamentals}} \cdot \underbrace{\frac{(\hat{p}_{90,b} - \hat{p}_{10,b}) + (\hat{e}_{90,t} - \hat{e}_{10,t})}{(\hat{p}_{90,b} - \hat{p}_{10,b}) + (\hat{e}_{90,b} - \hat{e}_{10,b})}}_{\text{Changes in residuals}}$$

This decomposition is an accounting identity, and it does not identify a causal effect of changes in fundamentals. The decomposition is not unique. We could obtain a similar decomposition by fixing the residuals at the levels observed in the first year, and allowing the fitted values to vary. In this case, we would have

$$\frac{D_t}{D_b} = \underbrace{\frac{(\hat{p}_{90,t} - \hat{p}_{10,t}) + (\hat{e}_{90,t} - \hat{e}_{10,t})}{(\hat{p}_{90,t} - \hat{p}_{10,t}) + (\hat{e}_{90,b} - \hat{e}_{10,b})}}_{\text{Changes in residuals}'} \cdot \underbrace{\frac{(\hat{p}_{90,t} - \hat{p}_{10,t}) + (\hat{e}_{90,b} - \hat{e}_{10,b})}{(\hat{p}_{90,b} - \hat{p}_{10,b}) + (\hat{e}_{90,b} - \hat{e}_{10,b})}}_{\text{Changes in fundamentals}'}$$

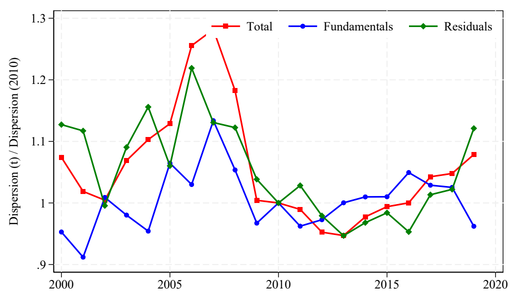
Both approaches are valid, but they might yield different values. To avoid arbitrary choices, we use the geometric mean of both to measure the contribution of macroeconomic components and residual components.

This approach can be extended to the percentile-based measures of skewness and kurtosis. For simplicity we decompose exact kurtosis, and not excess kurtosis as shown in the previous section. The derivations can be found in Appendix B. However, decomposing Kelley skewness presents additional difficulties since this measure can be negative. When the values in two periods (or counterfactuals) are of opposite signs, the ratio statistic lacks an interpretation. When this situation arises, we do not perform the decomposition. This limitation implies that the computed decompositions depend on which year acts as a base: picking a year where skewness was negative would result in fewer admissible comparisons than picking a year where it was positive, as 2010.

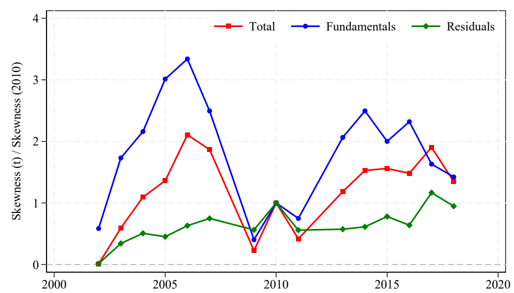
The results of the decomposition for the three statistics are presented in Figure 14. We selected 2010 as a reference year, since it is in the middle of the sample.

These lines represent the evolution of statistics when only macroeconomic components or residual components change. Of the three statistics, year-to-year movements in dispersion appear to be more closely linked to fundamentals — its level, as noted above, is close to that of other GRID countries: in several periods, the blue line (changes due to fundamentals) co-moves closely with the red line (actual changes), although this is a visual, in-sample comparison rather than a formal fit statistic, and the two lines diverge more noticeably in other periods. The co-movement is particularly evident in the aftermath of the global financial crisis, when the Polish economy experienced a slowdown. In 2019, residuals become relevant again, which is likely linked to the pandemic.

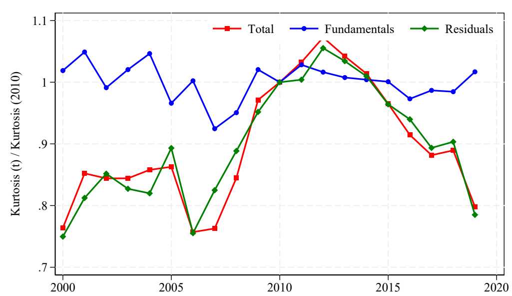
Figure 14: Decomposing changes in income growth



(a) Evolution of Dispersion
(2010=1)



(b) Evolution of Skewness
(2010=1)



(c) Evolution of Exact Kurtosis
(2010=1)

Notes: Each panel shows the actual evolution of the statistic relative to its 2010 value, together with the two multiplicative counterfactual components (fundamentals and residuals) described in the text; the two components multiply to give the actual value in every year. The decomposition is an in-sample accounting identity and is not unique. Years in which the skewness ratio is not well defined, because the numerator changes sign relative to the base year, are omitted from Panel (b).

For higher order moments, macroeconomic variables are less important. In the case of skewness, the term related to macroeconomic variables predicts substantially larger changes than those observed in the data. Only in years around 2010 (base year) is the change attributed to macroeconomic variables close to the actual change. Finally, changes in kurtosis appear to be unrelated to changes in macroeconomic variables, and instead are mostly attributed to the unexplained residual component. This failure of macroeconomic variables to predict changes in kurtosis reflects the limitations of the percentile-regression models discussed in the previous section, including their comparatively poor fit for the lower percentiles that underlie the kurtosis calculation.

6 Conclusions

This work described the implementation of statistics from the GRID project in Poland using Personal Income Tax data. Poland, like other countries of the second phase, experienced substantial transformations in the almost twenty years under study. We observed periods of strong out-migration and a high unemployment rate, which were coupled with an almost uninterrupted growth of GDP and minimum wages. These features suggested that earnings dynamics might differ from those presented in countries from the first phase of GRID. Our results show where Poland's distinctive context matters and where it does not. It is visible in the location and lower tail of the cross-sectional distribution, which compressed as the minimum wage rose and unemployment fell, and in the cyclical asymmetry of earnings changes; it is not visible in the level of dispersion of individual earnings changes, which resembles that documented in more mature economies.

The analysis of income inequality highlights developments characteristic of Poland. First, during the early years of the sample, Poland experienced earnings growth that surpassed that in more mature European economies, such as Germany (Drechsel-Grau et al. 2022) or France (Kramarz et al. 2022), and was similar to that in Norway (Halvorsen et al. 2022), over similar periods. Over the entire period, this growth did not increase income inequality: by 2020 measures of dispersion and Gini coefficient were below the levels from 2000. However, focusing only on the end points misses two distinct periods: an initial increase in inequality that lasted till 2005, and a rapid closing of the gap. The decline coincided with a tightening labor market and substantial increases in the real minimum wage. The percentile regressions are consistent with both developments contributing to lower-tail compression, but they do not identify causal effects.

Our analysis of earnings dynamics shows that Poland exhibits similar patterns to those observed in more developed countries. We observe deviations from normality of earnings changes similar to those reported in Guvenen et al. (2022). Moreover, the asymmetry of annual earnings changes co-moves with macroeconomic conditions, even if in Poland crises were relatively mild, while their overall dispersion is comparatively stable. Finally, our analysis of income growth at different percentiles of permanent income revealed a similar hockey-stick pattern as countries from the first phase. In spite of these similar income dynamics, Poland appears to have less income mobility than countries from the first phase. Income ranks appear to be more persistent, particularly among higher earners.

To connect these descriptive patterns to Poland's macroeconomic experience, we estimated percentile-level regressions relating changes in the earnings distribution to changes in the real minimum wage, unemployment, and real GDP. Growth in the real minimum wage is strongly associated with increases in the lower earnings percentiles, and the coefficients decline toward the top of the distribution. This gradient is consistent with compression of the cross-sectional earnings distribution. Increases in unemployment are associated with lower earnings across the distribution, although the magnitude of this relationship varies across percentiles. By contrast, the relationships between GDP growth and earnings percentiles are generally estimated less precisely.

We also examined percentiles of the distribution of individual earnings changes. In the joint specification, minimum-wage growth is associated with a leftward movement of the lower tail and a rightward movement of the upper tail, a pattern consistent with greater dispersion of earnings changes. The estimates at the extreme lower tail are imprecise, however. Higher unemployment is associated with a broad leftward shift in the earnings-change distribution, while the estimated relationships with GDP growth are sensitive to specification. An accounting decomposition suggests that the fitted component associated with the three macroeconomic variables co-moves more closely, in sample, with changes in the dispersion of earnings growth than with changes in skewness or kurtosis. Variation in these higher-order moments remains largely in the residual component.

These findings should be interpreted as descriptive associations rather than causal effects. The analysis relies on only twenty annual changes, and the minimum wage, unemployment, GDP, and earnings outcomes may respond jointly to other economic and policy developments. Moreover, the administrative data cover formal labor earnings among individuals who satisfy the GRID sample restrictions. Changes in employment intensity, migration, self-employment, reporting behavior, and workforce composition may therefore influence the estimated relationships.

Several questions remain for future research. Estimating these relationships jointly by gender and permanent-income rank would reveal whether the pooled results conceal important heterogeneity. Combining the tax records with information from the Structure of Earnings Survey or the Labor Force Survey could help quantify the role of sectoral and workforce composition and distinguish changes in wage rates from changes in months or hours worked. Where child-related tax information is available, it could also be used to test directly whether family formation contributes to the gender differences documented in the paper, rather than inferring this mechanism from age and gender profiles alone. Finally, applying the same percentile-based framework to other GRID countries would show which relationships are distinctive to Poland, while research designs using more plausibly exogenous variation would be needed to identify causal effects.

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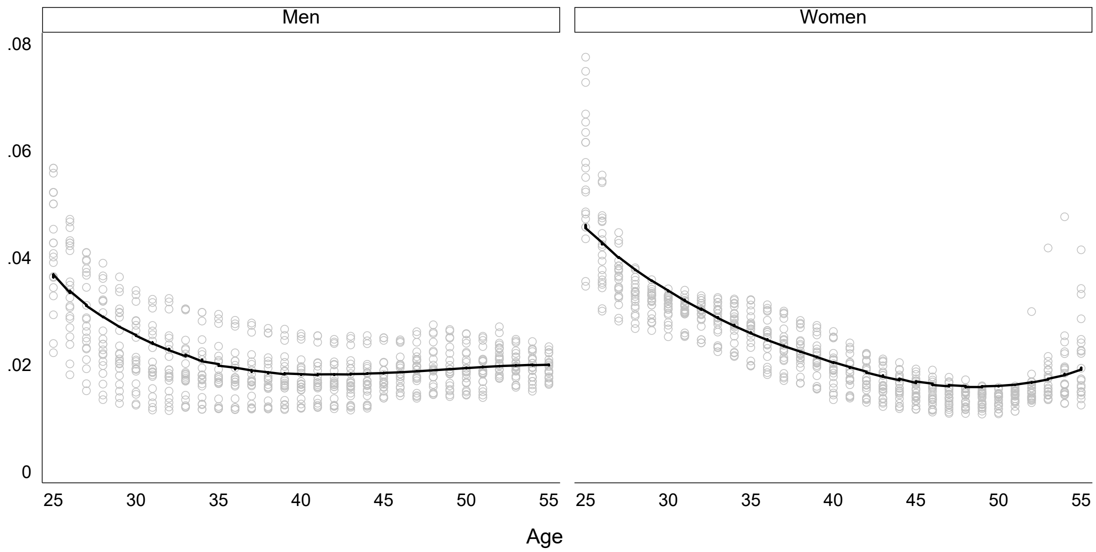
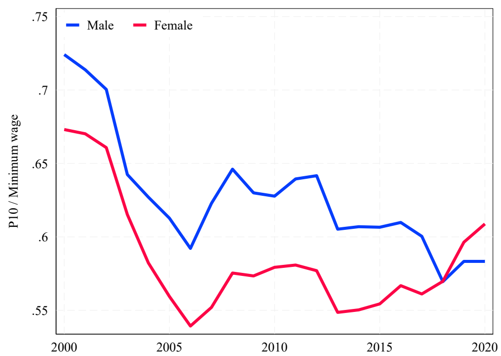
A Additional figures and tables

Figure A1: Proportion of individuals with earnings below GRID threshold

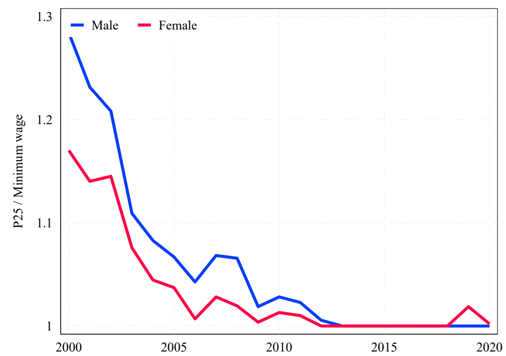


Notes: Percentage of individuals in the PIT database with incomes below the threshold defined by GRID, by gender and age.

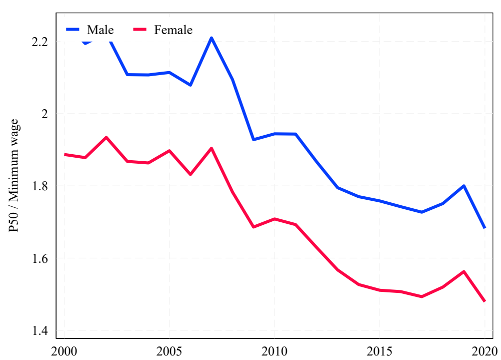
Figure A2: Minimum wages and percentiles of income distribution



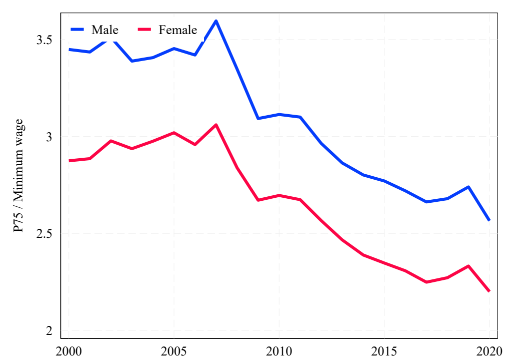
(a) 10th percentile



(b) 25th percentile



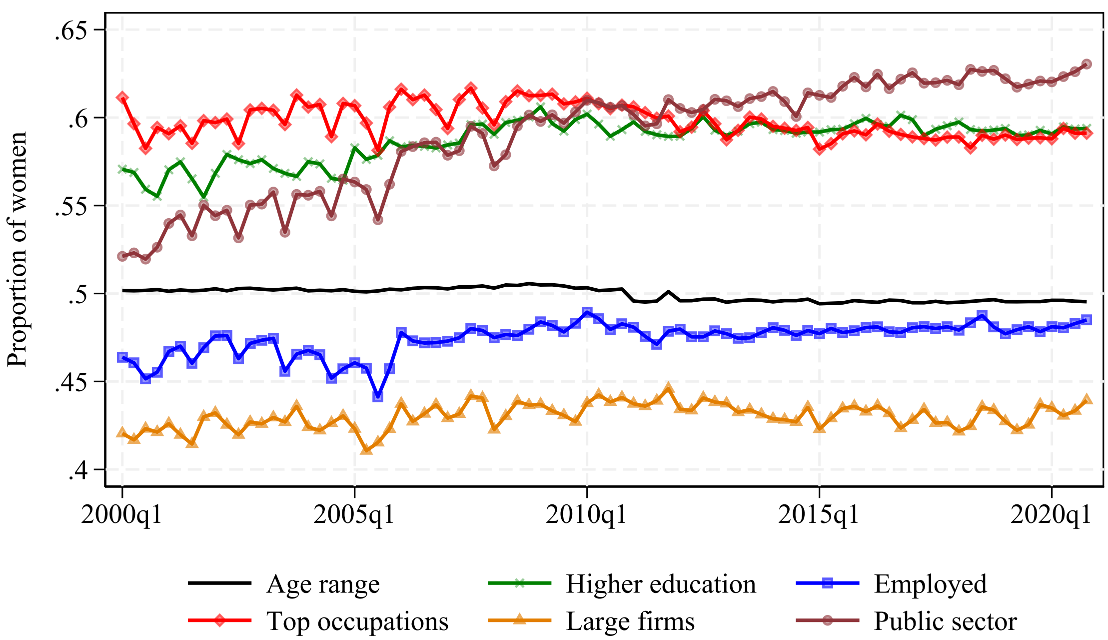
(c) 50th percentile



(d) 75th percentile

Notes: The figure shows the evolution of the ratios of different percentiles of the income distribution of men and women to the annualized minimum wage.

Figure A3: Proportion of women conditional on selected characteristics



Notes: The figure shows the proportion of women aged 25-55 conditional on selected characteristics: having tertiary studies ('Higher education'), being employed ('Employed'), working in an occupation with an ISCO code 1, 2 or 3 ('Top occupations'), working in a firm with more than 50 workers ('Large firms'), and working in the public sector ('Public sector'). All estimates are computed from LFS data for Poland. The jump in 2006 reflects an adjustment in the weighting variable.

Table A1: Annual changes in cross-sectional log-earnings quantiles and macroeconomic indicators.

	One variable at a time			All included		
	Unemp.	Min. Wage	GDP	Unemp.	Min. Wage	GDP
P1						
X variable	-0.0115*	1.186***	-0.400	-0.000869	1.220***	0.291
	(0.00613)	(0.0612)	(0.489)	(0.00270)	(0.0898)	(0.209)
R-squared	0.170	0.928	0.027		0.947	
P2.5						
X variable	-0.00999	1.151***	-0.638	-0.00400	1.063***	-0.208
	(0.00641)	(0.0468)	(0.458)	(0.00244)	(0.0748)	(0.190)
R-squared	0.130	0.891	0.071		0.899	
P5						
X variable	-0.0117*	1.289***	-0.594	-0.00285	1.252***	0.0111
	(0.00665)	(0.0864)	(0.585)	(0.00490)	(0.160)	(0.383)
R-squared	0.129	0.800	0.044		0.807	
P10						
X variable	-0.0125*	1.229***	-0.506	-0.00492	1.151***	-0.0731
	(0.00641)	(0.115)	(0.565)	(0.00473)	(0.167)	(0.394)
R-squared	0.150	0.750	0.033		0.766	
P12.5						
X variable	-0.0129**	1.180***	-0.445	-0.00633	1.072***	-0.135
	(0.00608)	(0.122)	(0.524)	(0.00420)	(0.160)	(0.356)
R-squared	0.172	0.739	0.027		0.764	
P25						
X variable	-0.0108**	0.956***	-0.457	-0.00881**	0.762***	-0.467**
	(0.00440)	(0.0612)	(0.438)	(0.00341)	(0.103)	(0.232)
R-squared	0.190	0.759	0.045		0.805	
P37.5						
X variable	-0.0102***	0.554***	0.0337	-0.00854***	0.410***	-0.174
	(0.00231)	(0.0754)	(0.380)	(0.00303)	(0.0970)	(0.274)
R-squared	0.310	0.472	0.000		0.607	
P50						
X variable	-0.00999***	0.406***	0.213	-0.00860***	0.277***	-0.0779
	(0.00192)	(0.0899)	(0.329)	(0.00298)	(0.0950)	(0.244)
R-squared	0.411	0.351	0.025		0.584	

Continued on next page

	One variable at a time			All included		
	Unemp.	Min. Wage	GDP	Unemp.	Min. Wage	GDP
P62.5						
X variable	-0.00898***	0.337***	0.248	-0.00728**	0.238**	0.00372
	(0.00177)	(0.0875)	(0.296)	(0.00299)	(0.0964)	(0.233)
R-squared	0.418	0.303	0.043		0.554	
P75						
X variable	-0.00730***	0.293***	0.187	-0.00561**	0.220**	0.0204
	(0.00153)	(0.0729)	(0.268)	(0.00273)	(0.0890)	(0.233)
R-squared	0.359	0.298	0.031		0.503	
P87.5						
X variable	-0.00597***	0.242***	0.128	-0.00516**	0.164**	-0.0486
	(0.00135)	(0.0595)	(0.251)	(0.00222)	(0.0661)	(0.216)
R-squared	0.329	0.278	0.020		0.465	
P90						
X variable	-0.00546***	0.223***	0.107	-0.00491**	0.146**	-0.0659
	(0.00138)	(0.0575)	(0.234)	(0.00215)	(0.0635)	(0.205)
R-squared	0.307	0.265	0.016		0.440	
P95						
X variable	-0.00486***	0.170***	0.128	-0.00456**	0.0989*	-0.0556
	(0.00157)	(0.0564)	(0.193)	(0.00216)	(0.0568)	(0.162)
R-squared	0.299	0.188	0.028		0.378	
P97.5						
X variable	-0.00506***	0.154**	0.154	-0.00503**	0.0750	-0.0691
	(0.00187)	(0.0637)	(0.176)	(0.00241)	(0.0600)	(0.155)
R-squared	0.297	0.143	0.037		0.348	
P99						
X variable	-0.00513**	0.0945	0.251	-0.00483*	0.0304	0.0117
	(0.00235)	(0.0793)	(0.158)	(0.00282)	(0.0672)	(0.161)
R-squared	0.282	0.049	0.090		0.285	
N	20.000	20.000	20.000		20.000	
F-statistic (Test 1)	58.01***	3492.48***	126.32***	23.06***	3821.728***	26.959***
F-statistic (Test 2)	41.13***	1715.22***	103.94***	20.16***	721.34***	4.32***

Notes: Columns 1–3 report three separate single-variable systems: in each, only the variable in the column header enters the regressions. Columns 4–6 report one joint system in which all three variables enter together. All specifications include a constant (not reported). Robust standard errors in parentheses. F-statistic (Test 1) is a test of joint significance of all coefficients in a column; F-statistic (Test 2) is a test of equality of coefficients across percentiles. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A2: Annual changes in cross-sectional log-earnings quantiles and macroeconomic indicators: comparison of coefficients

	$\beta^{90} - \beta^{10}$	$\beta^{90} - \beta^{50}$	$\beta^{50} - \beta^{10}$
Unemployment	0.000	0.004**	-0.004
	(0.004)	(0.002)	(0.003)
Minimum wage	-1.004***	-0.130**	-0.874***
	(0.140)	(0.053)	(0.104)
GDP	0.007	0.012	-0.005
	(0.376)	(0.148)	(0.316)

Notes: Table displays the difference between coefficients estimated at the 90^{th}, 50^{th} and 10^{th} percentiles for each right hand side variable. Estimates are based on columns 4-6 from Table A1. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Figure A4: Relationship between macroeconomic indicators and income percentiles by gender

(a) Changes in (log) minimum wages

(b) Changes in unemployment rate

(c) Changes in (log) GDP

Notes: Each panel plots the estimated coefficients across percentiles p of the cross-sectional log-earnings distribution for men and women separately (two regressions). The specification is identical to the joint seemingly-unrelated-regression system described in the text ($N = 20$ annual observations, 2000–2020). Vertical bars denote 90% confidence intervals.

Table A3: Quantiles of one-year residualized log-earnings changes and macroeconomic indicators

	One variable at a time			All included		
	Unemp.	Min. Wage	GDP	Unemp.	Min. Wage	GDP
P1						
X variable	-0.0168	0.224	0.260	-0.0339*	-0.532	-1.868
	(0.0129)	(0.587)	(1.015)	(0.0196)	(0.860)	(1.444)
R-squared	0.099	0.009	0.003		0.155	
P2.5						
X variable	-0.0187*	0.172	0.459	-0.0359**	-0.604	-1.822
	(0.0101)	(0.455)	(0.865)	(0.0159)	(0.659)	(1.178)
R-squared	0.164	0.007	0.013		0.238	
P5						
X variable	-0.0196**	0.173	0.653	-0.0334**	-0.507	-1.433
	(0.00818)	(0.354)	(0.705)	(0.0129)	(0.528)	(0.931)
R-squared	0.249	0.010	0.037		0.313	
P10						
X variable	-0.0124***	-0.0662	0.693**	-0.0201***	-0.443*	-0.649
	(0.00430)	(0.187)	(0.305)	(0.00656)	(0.254)	(0.431)
R-squared	0.355	0.005	0.148		0.472	
P12.5						
X variable	-0.0100**	-0.129	0.661***	-0.0164***	-0.426**	-0.470
	(0.00387)	(0.158)	(0.247)	(0.00545)	(0.211)	(0.354)
R-squared	0.314	0.027	0.183		0.472	
P25						
X variable	-0.00508*	-0.149	0.419***	-0.00911***	-0.314**	-0.256
	(0.00273)	(0.0973)	(0.150)	(0.00322)	(0.136)	(0.218)
R-squared	0.198	0.088	0.181		0.431	
P37.5						
X variable	-0.00420**	-0.0857	0.338***	-0.00638***	-0.191**	-0.118
	(0.00185)	(0.0633)	(0.119)	(0.00203)	(0.0875)	(0.150)
R-squared	0.264	0.057	0.229		0.448	
P50						
X variable	-0.00454***	0.00395	0.289**	-0.00541***	-0.0773	-0.0467
	(0.00105)	(0.0489)	(0.141)	(0.00118)	(0.0527)	(0.140)
R-squared	0.493	0.000	0.267		0.542	

Continued on next page

	One variable at a time			All included		
	Unemp.	Min. Wage	GDP	Unemp.	Min. Wage	GDP
P62.5						
X variable	-0.00536***	0.0283	0.342	-0.00550**	-0.0433	0.0223
	(0.00138)	(0.0574)	(0.233)	(0.00212)	(0.0456)	(0.229)
R-squared	0.444	0.006	0.242		0.462	
P75						
X variable	-0.00869***	0.00979	0.685**	-0.00679**	-0.0355	0.302
	(0.00231)	(0.104)	(0.304)	(0.00312)	(0.0714)	(0.293)
R-squared	0.505	0.000	0.420		0.578	
P87.5						
X variable	-0.0189***	0.267	1.227**	-0.0127**	0.198	0.668
	(0.00358)	(0.221)	(0.560)	(0.00525)	(0.148)	(0.441)
R-squared	0.670	0.069	0.379		0.709	
P90						
X variable	-0.0244***	0.417	1.486**	-0.0165***	0.318*	0.800
	(0.00402)	(0.275)	(0.690)	(0.00608)	(0.179)	(0.497)
R-squared	0.720	0.108	0.357		0.760	
P95						
X variable	-0.0394***	0.732*	2.268**	-0.0280***	0.521**	1.090*
	(0.00447)	(0.403)	(0.988)	(0.00730)	(0.217)	(0.561)
R-squared	0.819	0.145	0.363		0.859	
P97.5						
X variable	-0.0430***	0.810**	2.402**	-0.0321***	0.530***	1.010*
	(0.00386)	(0.405)	(1.061)	(0.00668)	(0.196)	(0.582)
R-squared	0.853	0.156	0.356		0.888	
P99						
X variable	-0.0424***	0.841**	2.285**	-0.0321***	0.543***	0.899
	(0.00356)	(0.384)	(1.097)	(0.00577)	(0.142)	(0.579)
R-squared	0.854	0.173	0.332		0.890	
N	20.000	20.000	20.000		20.000	
F-statistic (Test 1)	302.985***	1623.808***	1214.675***	468.549***	9303.185***	454.005***
F-statistic (Test 2)	198.895***	1612.199***	1266.923***	130.051***	1906.513***	347.046***

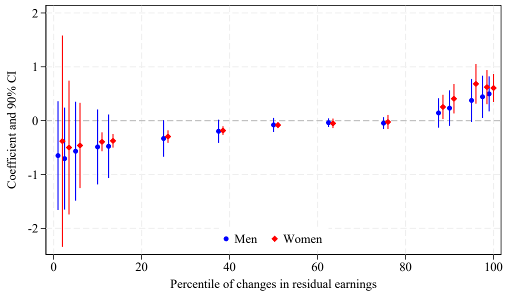
Notes: Notes: Columns 1–3 report three separate single-variable systems: in each, only the variable in the column header enters the regressions. Columns 4–6 report one joint system in which all three variables enter together. All specifications include a constant (not reported). Robust standard errors in parentheses. F-statistic (Test 1) is a test of joint significance of all coefficients in a column; F-statistic (Test 2) is a test of equality of coefficients across percentiles. * p¡0.1, ** p¡0.05, *** p¡0.01.

Table A4: Quantiles of one-year residualized log-earnings changes and macroeconomic indicators: evaluating differences in coefficients

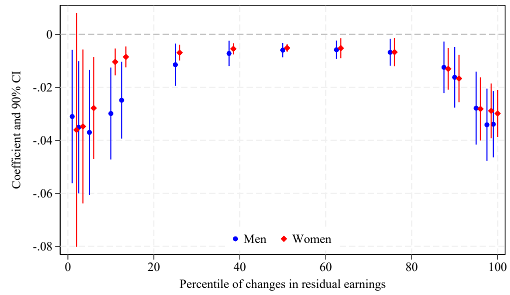
	$\beta^{90} - \beta^{10}$	$\beta^{90} - \beta^{50}$	$\beta^{50} - \beta^{10}$
Unemployment	0.004	-0.011*	0.015**
	(0.012)	(0.006)	(0.006)
Minimum wage	0.761*	0.395*	0.366*
	(0.424)	(0.217)	(0.215)
GDP	1.449*	0.847*	0.602
	(0.800)	(0.456)	(0.394)

Notes: Table displays the difference between coefficients estimated at the 90^{th}, 50^{th} and 10^{th} percentiles for each right hand side variable. Estimates are based on columns 4-6 from Table A3. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

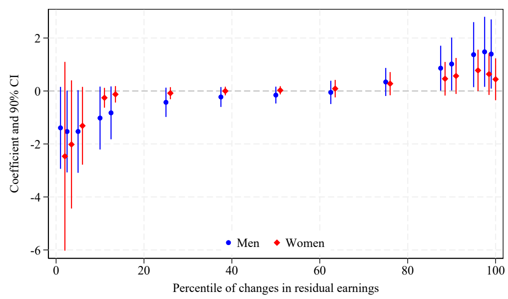
Figure A5: Macroeconomic associations across quantiles of individual one-year earnings changes by gender



(a) Changes in (log) minimum wages



(b) Changes in unemployment rate



(c) Changes in (log) GDP

Notes: Each panel plots the estimated coefficients across percentiles p of the distribution of individual one-year residualized earnings changes for men and women separately. The specification is identical to the joint seemingly-unrelated-regression system described in the text ($N = 20$ annual observations, 2000–2020). Vertical bars denote 90% confidence intervals.

B Decomposition of Skewness and Kurtosis

Section 5.3 from the main text derived a decomposition of changes in dispersion, D_t/D_b, into a component driven by changes in economic fundamentals and a component driven by changes in the residuals, using the fitted/residual split $p_{p,t} = \hat{p}_{p,t} + \hat{e}_{p,t}$ for each percentile p. Kelley skewness and Crow–Siddiqui kurtosis are both ratios of percentile differences, exactly like D_t, so the same accounting logic applies – with one additional step, since skewness and kurtosis are each a *ratio of two such differences* rather than a single difference.

B.1 Skewness

Kelley skewness at time t is

$$S_t = \frac{p_{90,t} + p_{10,t} - 2p_{50,t}}{p_{90,t} - p_{10,t}} =: \frac{N_t}{D_t},$$

where $N_t := p_{90,t} + p_{10,t} - 2p_{50,t}$ and D_t is the interdecile range defined as in the dispersion section. Growth in skewness between the base period b and end period t is

$$\frac{S_t}{S_b} = \frac{N_t/N_b}{D_t/D_b}.$$

Because N_t and D_t are each additive in $\hat{p}_p$ and $\hat{e}_p$, they admit the same counterfactual decomposition used for dispersion. Using the fitted/residual split, and holding the residuals fixed at their period-t values while letting fitted values move from b to t:

$$\frac{N_t}{N_b} = \underbrace{\frac{(\hat{p}_{90,t} - 2\hat{p}_{50,t} + \hat{p}_{10,t}) + (\hat{e}_{90,t} - 2\hat{e}_{50,t} + \hat{e}_{10,t})}{(\hat{p}_{90,b} - 2\hat{p}_{50,b} + \hat{p}_{10,b}) + (\hat{e}_{90,t} - 2\hat{e}_{50,t} + \hat{e}_{10,t})}}_{\text{Changes in fundamentals } (N)} \cdot \underbrace{\frac{(\hat{p}_{90,b} - 2\hat{p}_{50,b} + \hat{p}_{10,b}) + (\hat{e}_{90,t} - 2\hat{e}_{50,t} + \hat{e}_{10,t})}{(\hat{p}_{90,b} - 2\hat{p}_{50,b} + \hat{p}_{10,b}) + (\hat{e}_{90,b} - 2\hat{e}_{50,b} + \hat{e}_{10,b})}}_{\text{Changes in residuals } (N)},$$

and, as in the dispersion section,

$$\frac{D_t}{D_b} = \underbrace{\frac{(\hat{p}_{90,t} - \hat{p}_{10,t}) + (\hat{e}_{90,t} - \hat{e}_{10,t})}{(\hat{p}_{90,b} - \hat{p}_{10,b}) + (\hat{e}_{90,t} - \hat{e}_{10,t})}}_{\text{Changes in fundamentals } (D)} \cdot \underbrace{\frac{(\hat{p}_{90,b} - \hat{p}_{10,b}) + (\hat{e}_{90,t} - \hat{e}_{10,t})}{(\hat{p}_{90,b} - \hat{p}_{10,b}) + (\hat{e}_{90,b} - \hat{e}_{10,b})}}_{\text{Changes in residuals } (D)}.$$

Combining the two, growth in skewness decomposes as

$$\frac{S_t}{S_b} = \underbrace{\left(\frac{\text{Changes in fundamentals } (N)}{\text{Changes in fundamentals } (D)}\right)}_{\text{Changes in fundamentals}} \cdot \underbrace{\left(\frac{\text{Changes in residuals } (N)}{\text{Changes in residuals } (D)}\right)}_{\text{Changes in residuals}}.$$

As with dispersion, this decomposition is not unique: freezing the residuals at their period-b values in both N and D, and letting the fitted values move, gives an equally valid alternative decomposition,

$$\frac{N_t}{N_b} = \underbrace{\frac{(\hat{p}_{90,t} - 2\hat{p}_{50,t} + \hat{p}_{10,t}) + (\hat{e}_{90,t} - 2\hat{e}_{50,t} + \hat{e}_{10,t})}{(\hat{p}_{90,t} - 2\hat{p}_{50,t} + \hat{p}_{10,t}) + (\hat{e}_{90,b} - 2\hat{e}_{50,b} + \hat{e}_{10,b})}}_{\text{Changes in residuals}' \ (N)} \cdot \underbrace{\frac{(\hat{p}_{90,t} - 2\hat{p}_{50,t} + \hat{p}_{10,t}) + (\hat{e}_{90,b} - 2\hat{e}_{50,b} + \hat{e}_{10,b})}{(\hat{p}_{90,b} - 2\hat{p}_{50,b} + \hat{p}_{10,b}) + (\hat{e}_{90,b} - 2\hat{e}_{50,b} + \hat{e}_{10,b})}}_{\text{Changes in fundamentals}' \ (N)},$$

with D_t/D_b decomposed as in the main text, and the two ratios combined as above to give Changes in fundamentals′ and Changes in residuals′ for skewness.

Unlike dispersion, N_t (and S_t) can change sign across periods. When N_t and N_b (or the corresponding counterfactual numerator) have opposite signs, the ratio N_t/N_b no longer has a growth-rate interpretation. In periods where this occurs, we do not compute the skewness decomposition.

B.2 Kurtosis

Crow–Siddiqui kurtosis at time t is

$$K_t = \frac{p_{97.5,t} - p_{2.5,t}}{p_{75,t} - p_{25,t}} =: \frac{N_t^K}{D_t^K}.$$

Both N_t^K and D_t^K are interpercentile ranges of exactly the same form as D_t in the dispersion decomposition, so each decomposes in the same way, with fundamentals holding the residuals fixed at period t and residuals holding the fitted values fixed at period b:

$$\frac{N_t^K}{N_b^K} = \underbrace{\frac{(\hat{p}_{97.5,t} - \hat{p}_{2.5,t}) + (\hat{e}_{97.5,t} - \hat{e}_{2.5,t})}{(\hat{p}_{97.5,b} - \hat{p}_{2.5,b}) + (\hat{e}_{97.5,t} - \hat{e}_{2.5,t})}}_{\text{Changes in fundamentals } (N^K)} \cdot \underbrace{\frac{(\hat{p}_{97.5,b} - \hat{p}_{2.5,b}) + (\hat{e}_{97.5,t} - \hat{e}_{2.5,t})}{(\hat{p}_{97.5,b} - \hat{p}_{2.5,b}) + (\hat{e}_{97.5,b} - \hat{e}_{2.5,b})}}_{\text{Changes in residuals } (N^K)},$$

$$\frac{D_t^K}{D_b^K} = \underbrace{\frac{(\hat{p}_{75,t} - \hat{p}_{25,t}) + (\hat{e}_{75,t} - \hat{e}_{25,t})}{(\hat{p}_{75,b} - \hat{p}_{25,b}) + (\hat{e}_{75,t} - \hat{e}_{25,t})}}_{\text{Changes in fundamentals } (D^K)} \cdot \underbrace{\frac{(\hat{p}_{75,b} - \hat{p}_{25,b}) + (\hat{e}_{75,t} - \hat{e}_{25,t})}{(\hat{p}_{75,b} - \hat{p}_{25,b}) + (\hat{e}_{75,b} - \hat{e}_{25,b})}}_{\text{Changes in residuals } (D^K)}.$$

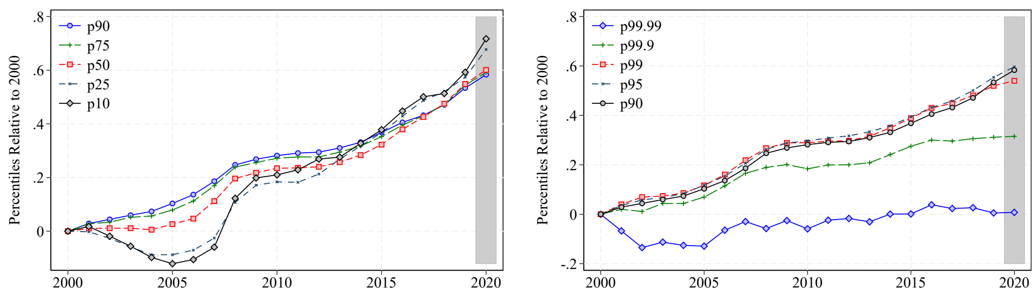
Combining as before,

$$\frac{K_t}{K_b} = \underbrace{\left(\frac{\text{Changes in fundamentals } (N^K)}{\text{Changes in fundamentals } (D^K)}\right)}_{\text{Changes in fundamentals}} \cdot \underbrace{\left(\frac{\text{Changes in residuals } (N^K)}{\text{Changes in residuals } (D^K)}\right)}_{\text{Changes in residuals}},$$

and, as in previous cases, an equally valid alternative decomposition is obtained by holding constant the residuals at period b and letting the fitted values move first in both N_t^K/N_b^K and D_t^K/D_b^K, giving Changes in fundamentals′ and Changes in residuals′.

C Additional Inequality Figures

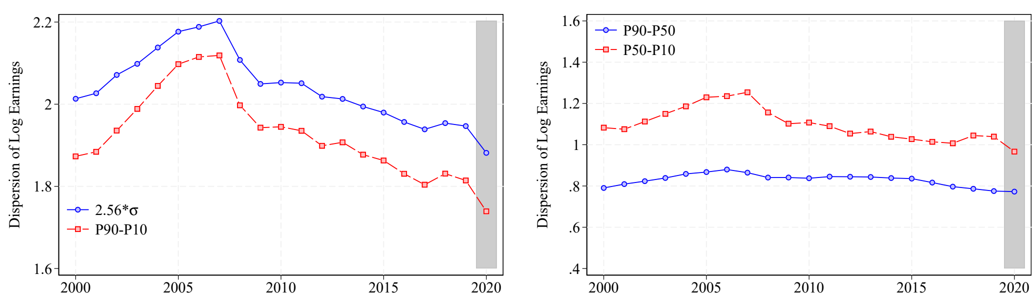
Figure C1: Change of Percentiles of the log real earnings distribution (pooled sample)



(a) Core percentiles (b) Top percentiles

Notes: Percentiles relative to 2000. Panel (a) shows core percentiles (P10, P25, P50, P75, P90). Panel (b) shows top percentiles (P90, P95, P99, P99.9, P99.99).

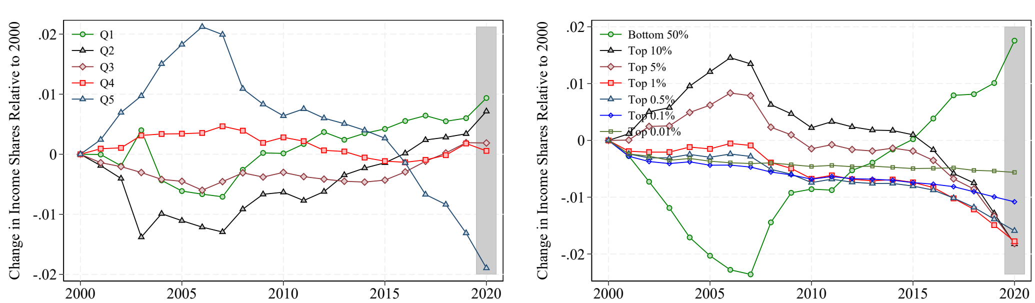
Figure C2: Earnings inequality (pooled sample)



(a) Dispersion (b) Bottom and top dispersion

Notes: Panel (a) shows overall dispersion measured by P90-P10 and standard deviation. Panel (b) shows bottom (P50-P10) and top (P90-P50) tail inequality.

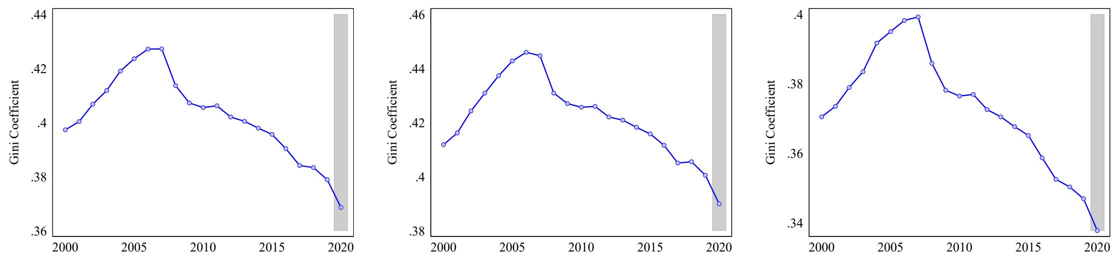
Figure C3: Changes in income shares relative to 2000



(a) Quintile shares (b) Selected percentiles

Notes: Changes in income shares relative to 2000.

Figure C4: Gini coefficient

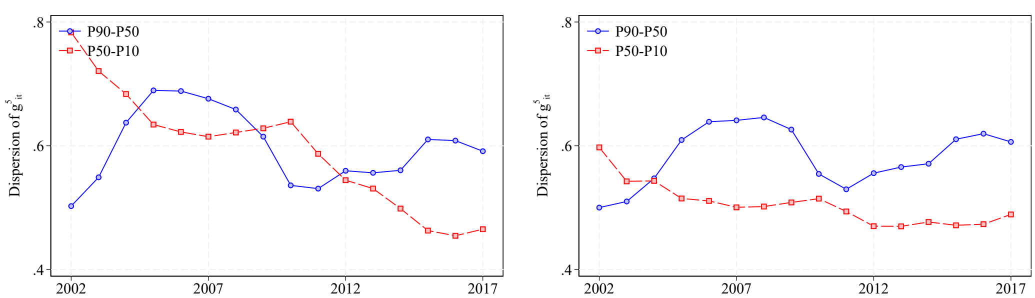


(a) All (b) Men (c) Women

Notes: Evolution of the Gini coefficient over time.

D Additional Earnings Dynamics Figures

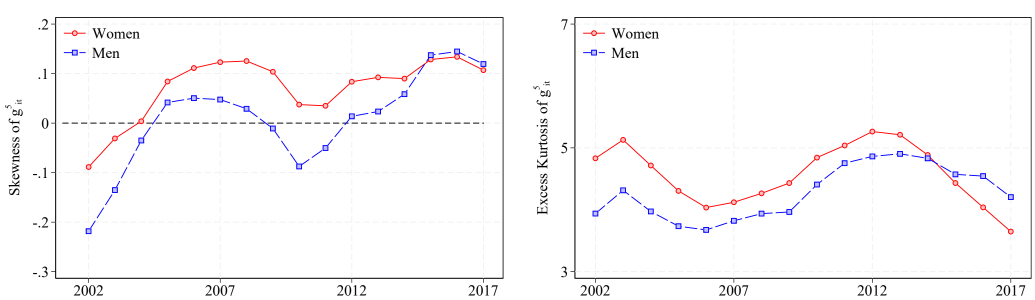
Figure D1: Dispersion of 5-year log earnings changes, by gender



(a) Men (b) Women

Notes: 5-year changes in residualized log earnings. Compare to Figure 8 for 1-year changes.

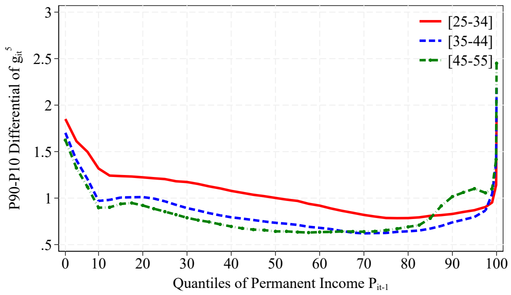
Figure D2: Higher moments of 5-year log earnings changes, by gender



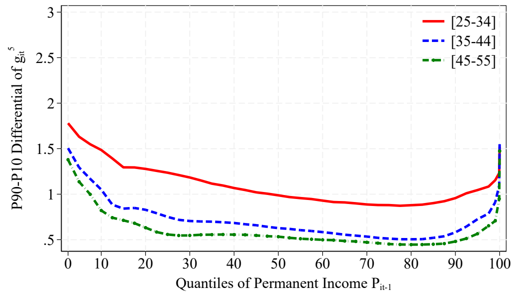
(a) Kelley Skewness (b) Excess Crow-Siddiqui Kurtosis

Notes: 5-year changes in residualized log earnings. Compare to Figure 9 for 1-year changes.

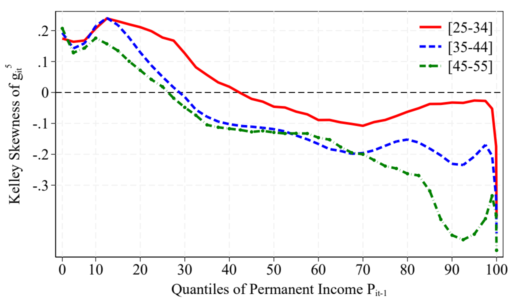
Figure D3: Dispersion, Skewness, and Kurtosis of 5-year log earnings changes by gender, age, and permanent income quantiles



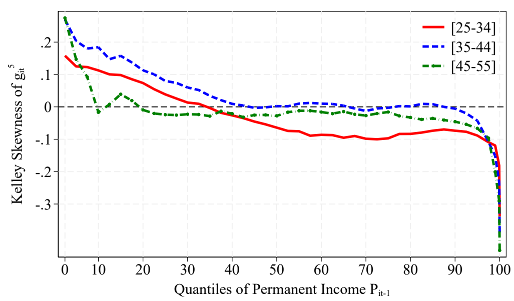
(a) Dispersion – Men



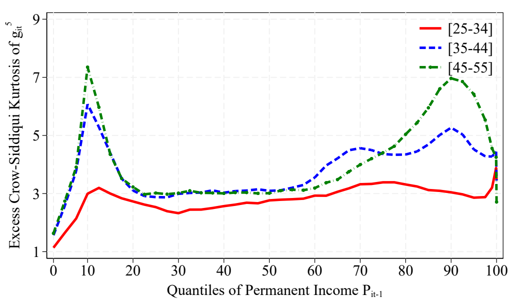
(b) Dispersion – Women



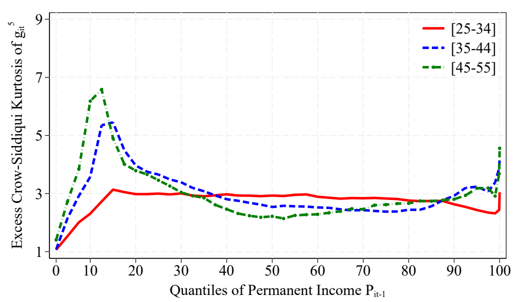
(c) Kelley Skewness – Men



(d) Kelley Skewness – Women



(e) Excess Crow-Siddiqui Kurtosis – Men

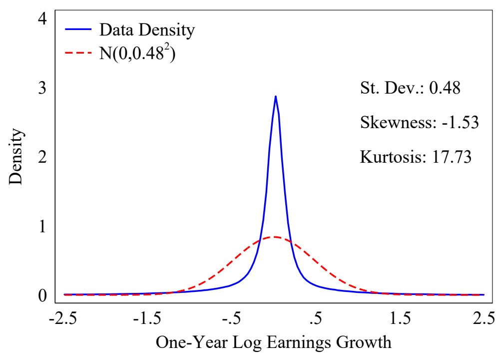


(f) Excess Crow-Siddiqui Kurtosis – Women

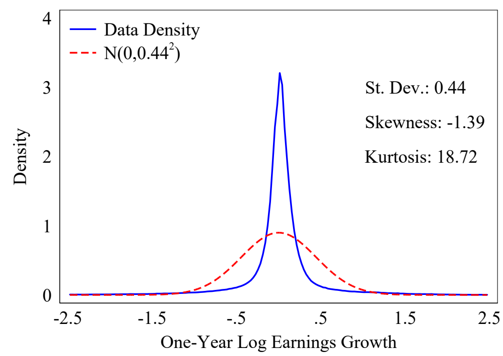
Notes: 5-year changes in residualized log earnings by permanent income quantiles. Permanent income is defined as the 3-year average of earnings. Lines correspond to different age groups: 25-34, 35-44, and 45-55. Compare to Figure 10 for 1-year changes.

D.1 Empirical densities of earnings growth

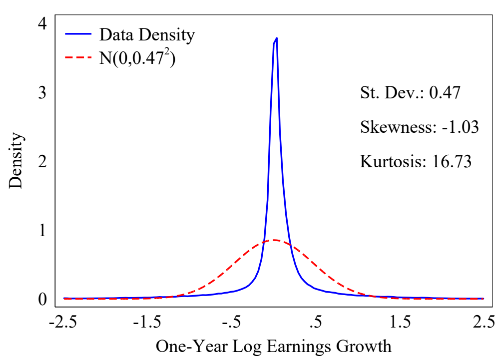
Figure D4: Distribution of 1-year earnings growth, by gender



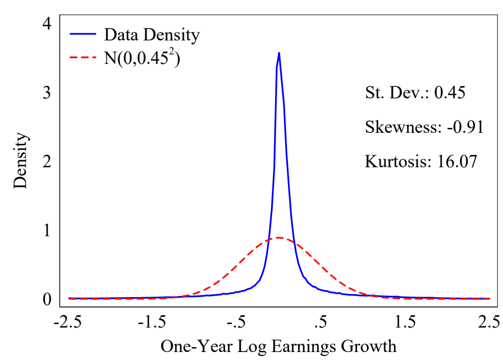
(a) Men, 2000



(b) Women, 2000



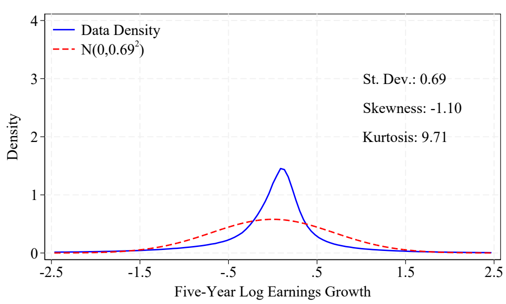
(c) Men, 2010



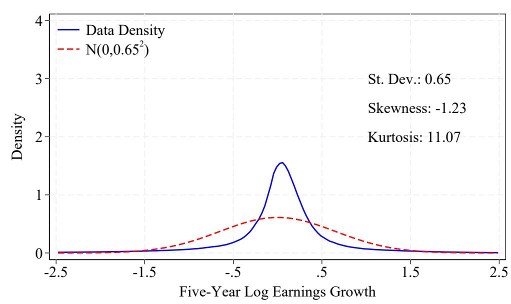
(d) Women, 2010

Notes: Kernel density estimates of 1-year changes in residualized log earnings. Figures present moment-based descriptive statistics.

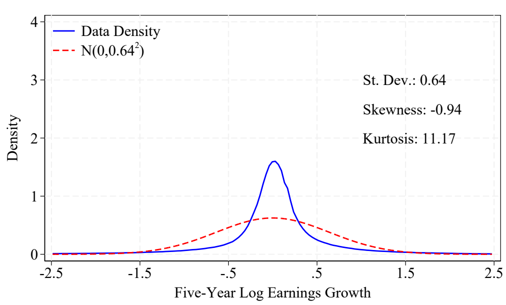
Figure D5: Distribution of 5-year earnings growth, by gender



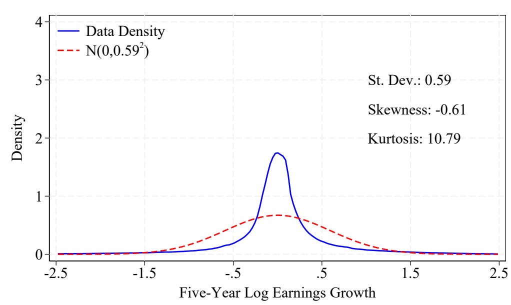
(a) Men, 2000



(b) Women, 2000



(c) Men, 2010



(d) Women, 2010

Notes: Kernel density estimates of 5-year changes in residualized log earnings. Figures present moment-based descriptive statistics.