Inequality and Earnings Dynamics in Finland: Regional and Sectoral Transitions 1987-2018*

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Abstract

Using administrative register data from 1987 to 2018, this paper studies the evolution of earnings inequality and income dynamics in Finland during a period of profound structural transformation. A severe economic crisis in the early 1990s brought about the deepest recession experienced in the Nordic region. The crisis triggered sharp increases in inequality as earnings at the bottom collapsed, and income dispersion remained elevated even after the aggregate recovery. We show that adjustment patterns differed markedly across regions and sectors. Rural areas saw a lasting decline in agriculture and low-tech manufacturing, but the expansion of social services and other low-skill services helped sustain low-income employment and reduce inequality. In Helsinki and other cities, growth was fueled by the IT sector and high-skill services, boosting top incomes and entrenching higher inequality. These results highlight how sectoral shocks and regional specialization can generate divergent trajectories of earnings inequality in the wake of a major economic crisis.

JEL Codes: D31, J31, R23

Keywords: Earnings inequality, earnings dynamics, regional inequality

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1 Introduction

It is well-documented that negative economic shocks tend to exacerbate income inequality (Guvenen et al., 2022). However, much less is understood about the dynamics of earnings volatility and the long-run adjustment process a country undergoes after a severe economic crisis. As the economy transitions from one equilibrium to another, the reallocation of workers is shaped by frictions in mobility – both geographic and sectoral. When shocks are regionally concentrated, the adjustment process highlights a tension between place-based protection and broader structural transformation. Understanding the tradeoffs between within-region and between-region inequality is therefore crucial for designing effective policies to mitigate the impacts of major economic disruptions.

This paper studies earnings inequality in Finland in two complementary parts. As part of the Global Repository of Income Dynamics (GRID) project,[1] the first part of the paper documents the evolution of earnings inequality and dynamics among prime-age workers between 1987 and 2018. Finland has historically maintained low earnings inequality compared to other developed economies.[2] However, the severe economic recession in the early 1990s marked a turning point in Finland's earnings inequality. The recession and the subsequent ICT-driven growth period, led by Nokia's emergence as a global market leader, both left long-lasting effects on the earnings distribution. We show that income inequality rose sharply during the 1991–1993 crisis, driven primarily by a deterioration in earnings at the bottom of the distribution. The earnings dispersion gradually declined in the late 1990s but never returned to its pre-crisis levels. Inequality in the upper half of the distribution remained relatively stable during crises, expanding only modestly after the 2000s, particularly among women.

We then examine earnings dynamics, measured as one-year earnings changes after conditioning on gender and age. The dispersion of earnings changes rose sharply during both the early 1990s crisis and the 2008 financial crisis. In both episodes, downside risks expanded rapidly while upside risks contracted (though to a lesser extent). We also find that the Kelley skewness of earnings changes is strongly pro-cyclical, becoming much more negatively skewed in downturns. Finally, excess Crow-Siddiqui kurtosis is consistently higher for women, reflecting extreme earnings fluctuations driven in part by child rearing-related labor supply changes. However, earnings mobility remains stable over time, indicating that the high mobility in Finland has not been affected by the rise in cross-sectional earnings inequality after the 1990s crisis.

In the second part of the paper, we examine the geographic dimension of inequality and reallocation during our observation period from 1987 to 2018. Spatial earnings inequality is particularly salient in Finland, where economic booms and busts have affected regions unevenly due to the heterogeneity in sectoral composition. In the early 1990s Finnish economy faced nationwide shocks (financial liberalization and stock market crash, banking crisis, European monetary contraction) while certain industries within manufacturing, concentrated in certain industrial towns, were especially hard hit by the Soviet trade collapse (Gulan et al., 2021; Costinot et al., 2024). The subsequent recovery period also had a spatial dimension: growth

[1] GRID aims to harmonize cross-country data from administrative registers to produce statistics on earnings dynamics. See Guvenen et al. (2022).

[2] See Jäntti et al. (2010) for a description of the evolution before 1987.

concentrated in ICT and high-tech industries in more urban areas. How did these uneven shocks across industries and regions translate into broader patterns of earnings inequality?

First, we decompose total earnings inequality into within-region and between-region components over time. We split the regions into three region types: the Helsinki (capital) area, other cities, and rural municipalities, which show distinct inequality trajectories. In the 1990s recession, income inequality rose sharply and persistently in the capital region, but declined after the recession in other cities and rural areas, in rural areas even to below pre-crisis levels. The growth in inequality in capital region was fueled by top incomes, while the bottom incomes stagnated. In contrast, periphery areas have seen much greater improvement in bottom incomes. These patterns remain even after accounting for demographic changes. Over time, mean incomes in rural regions grew at a faster rate than in the greater Helsinki region and other cities, implying a convergence in earnings between regions.

These regional differences are linked to structural changes in the industrial composition. In the Helsinki region, the expansion of high-paying sectors such as ICT, together with growth in low-wage service industries, widened both within- and between-industry inequality. In contrast, rural areas experienced shrinking employment in agriculture and low-tech manufacturing but rising wages among those who remained, leading to a modest overall decline in inequality. These findings highlight how regional sectoral restructuring and sector-specific dynamics have shaped the divergent trajectories of inequality since the early 1990s. These results can be interpreted as a spatial and sectoral demonstration of the job-polarization processes described in the large literature studying technological change and globalization and their effect on employment and wages (e.g. Autor et al., 2013; Goos et al., 2014).

This paper relates to a large literature on earnings dynamics, which in the past has mostly focused on the US experience (see, for example Guvenen et al. (2021)). Recently, the project on the Global Repository of Income Dynamics (GRID) has expanded the same methodology and data structure to 13 countries, which is summarized in Guvenen et al. (2022), while Brewer et al. (2025) provide a broader review of the literature. We contribute to this literature by bringing a case study of a small open economy with extensive social safety nets, a deep crisis, rapid technological expansion, and later stagnating growth. We also examine unemployment in the aftermath of the economic crisis, which is often overlooked in studies of earnings dynamics. However, as discussed in Heathcote et al. (2020), recessions can generate persistent non-participation and have lasting effects on earnings inequality.

More broadly, this paper is also related to earlier studies on earnings and income inequality in Finland. Paukkeri et al. (2024) examine the evolution of income inequality and its drivers, particularly the rise in inequality during the late 1990s, though they do not delve into earnings volatility or higher moments of the earnings distribution.[3] Whereas our paper takes a broader view on total earnings distribution and its evolution, a complementary strand of literature studies the effects of job loss on earnings utilizing quasi-experimental designs (e.g for Finland Korkeamäki and Kyyrä, 2014; Verho, 2020; Huttunen and Riukula, 2024). Additionally, by adding a regional dimension, this paper relates to works on spatial earnings dynamics and

[3]Paukkeri et al. (2023) is a broader working paper version of Paukkeri et al. (2024), part of the Country Studies project parallel to the IFS Deaton Review of Inequality, examining in depth the income inequalities in Finland over 1987-2021.

interregional inequality (Kramarz et al., 2022; Bathelt et al., 2024).

Evidence from the United States suggests that much of the change in overall earnings inequality over time can be explained by the rising dispersion between industries and there are only a few industries explaining the increase in between industry dispersion (Haltiwanger et al., 2024). These patterns are in accordance with models of skill-biased technological change and task automation (e.g. Autor and Dorn, 2013), which emphasize that local labor markets specialized in routine industries face sharper employment shifts. Building on this spatial perspective, we add to the prior literature by studying how the evolving regional industry mix contributes to differences in earnings dynamics and the development of spatial inequality. Kerr et al. (2020) and Maczulskij (2024) have studied occupational restructuring with Finnish data and shown sharper declines in routine jobs and rises in high-skill occupations, especially in firms engaged in outsourcing and trade.

The paper is structured as follows: In Section 2 we first describe the Finnish administrative data sources and the sample restrictions that follow the GRID project guidelines, as well as the Finnish institutional context and summary statistics. The main results are presented in two parts. The first set of results – earnings inequality, volatility and mobility in Finland during 1987–2018 – can be found in Section 3. Section 4 presents the second set of results, the regional and industry analysis. Section 5 concludes.

2 Data and institutional details

2.1 Data

We use administrative data covering the total of Finnish population for period 1987 to 2018. These administrative registers from various public authorities are collected and maintained by Statistics Finland. For example, the earnings and income data comes from Finnish Tax Administration, which collects this data directly from the employers or benefit providers. The data is accurate and reported at a granular level. Data include total wages (including bonuses, overtime pay etc.), self-employment income, paid leaves and realized stock options but it excludes payroll taxes paid by employer. Unless otherwise stated, our earnings measure relates to annual individual earnings from labor markets excluding self-employment income. Using personal identifiers, the data can be linked to background information in other datasets, such as time of birth, education, place of residence and employer's industry. Individuals disappear from these registers only in case of emigration or death.

All income variables are deflated using the consumer price index with base year 2018. The analysis is made in local currency, but in the paper, we illustrate monetary amounts in US dollars. We impose a few sample restrictions to harmonize the sample following the GRID database guidelines: we only include individuals who are aged 25–55 and whose annual earnings are above a minimum earnings threshold. The age restriction is done to focus on the time period after the education phase and before retirement – the "prime" working ages. The minimum earnings threshold ensures that we focus on individuals with meaningful labor-force attachment and can use log tansformations of earnings. In Section 4.2, we extend the analysis to unemployment, as extensive-margin dynamics are particularly relevant during recessions and across regions.

In Finland, there is no national minimum wage, so our minimum earnings threshold corresponds to 1.5 times the minimum monthly wage in retail industry jobs. For example, in 1987 individuals with total annual earnings less than 2,193 USD are dropped while this income limit is 3,151 USD in 2018. On average 5.5% of workers with positive earnings are dropped due to this restriction (between 80,000–140,000 individuals annually). After these restrictions we have approximately 1.7 million individuals in our sample yearly.

Key variables used in the analysis are raw log earnings, residual log earnings, and permanent log earnings. Residual log earnings ε_{it} are obtained by regressing real log earnings on a full set of age dummies separately for each year and gender and then saving the residuals. The residualization of earnings removes gender differences and life cycle specific variance in earnings. To further reduce the influence of transitory annual fluctuations in earnings, we use a permanent income measure: Permanent earnings P_{it} for an individual in year t are obtained by first calculating average earnings in years t, $t-1$ and $t-2$, then residualizing these log average earnings on age and gender for each year t. To be assigned a permanent earnings measure for year t, the individual can have income below the minimum earnings threshold at most in one year of the three years used in the calculation. Finally, in addition to earnings levels, a key ingredient in the analysis is earnings dynamics, which we study using individual (residualized) earnings changes 1 or 5 years forward, $g_{it}^{s} = \varepsilon_{it+s} - \varepsilon_{it}$. Here, individuals are required to have earnings at least one-third of the minimum threshold in year $t+1$ or $t+5$.

Table 1: Descriptive statistics for the cross-sectional sample

Year	Obs.	Mean Income		Share	Age Shares %			Education Shares %	
	(Mill)	Men	Women	Female %	[25,35]	[36,45]	[46,55]	Low	High
1987	1,817,298	34,839	24,735	48.6	40.1	37.1	22.8	67.8	32.2
2018	1,697,781	50,786	38,335	48.6	35.2	33.1	31.7	51.9	48.1

Year	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9
1987	2,873	5,914	10,109	20,173	27,399	35,957	47,397	57,051	85,366	150,763
2018	4,132	8,375	13,687	28,279	40,479	54,860	74,424	91,523	149,301	317,327

Note: Table 1 shows summary statistics for CS sample in 1987 and 2018. Income measures are reported in real 2018 USD. Education levels are divided into two categories: low (high school or less) and high (above high school).

We use three different samples in the analysis. First, we have a cross-sectional sample (CS) as defined above: 25–55-year-old workers with annual earnings above the minimum threshold. Second, the longitudinal sample (LX) includes all individuals in the cross-sectional sample who also have observations 1 and 5 years forward, so we can measure 1- and 5-year earnings changes.[4] Third, the heterogeneity sample (H) is a subset of the longitudinal sample, further narrowing to individuals for whom we have a measure of permanent earnings. The H sample is used to analyze the differential earnings dynamics along the income distribution, focusing on the latest 20 years of the data, and always pooling across the years.[5] Notice that for an individual in the base year t, we use the permanent earnings measure from year $t-1$ (P_{it-1}) while the earnings changes are measured between t and $t+1$ or $t+5$, thus avoiding mechanical correlation between the measures. The CS sample covers individuals in all years 1987–2018, the LX sample from

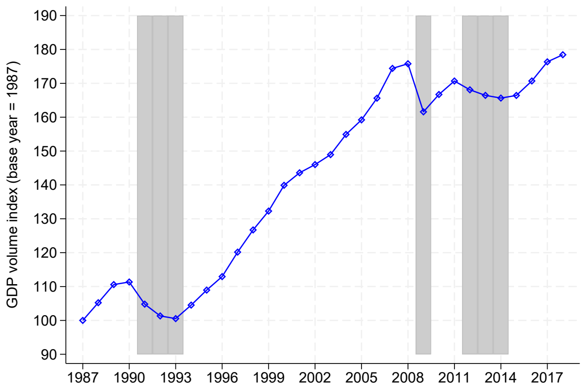
[4]In the analysis, earnings changes are always defined as forward changes.

[5]Due to changing demographics and societal changes over time, the heterogeneity analysis is restricted to a shorter time period, also enhancing comparability of results across countries.

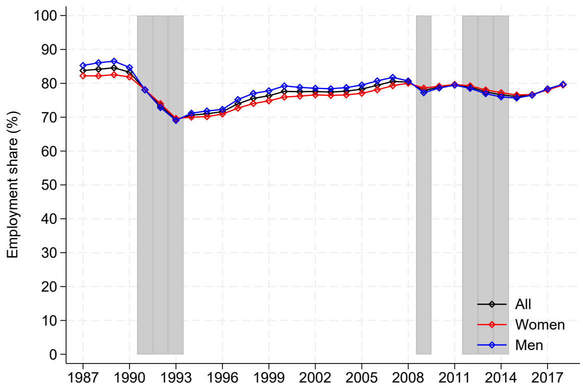
1987 to 2017 (1-year earnings changes) or 2013 (5-year earnings changes), and H sample from 1989 to 2013.

Table 1 presents summary statistics for the cross-sectional sample in the first and last years of the analysis period. The change in age composition illustrates the rapid aging of the Finnish population during the analysis period compared to many other OECD countries (OECD database, 2025a). At the same time, the education level increases considerably: the share of those with low education (at most high school education) decreases from 68% to 52%. For the median of the distribution, earnings have grown 48% over the 31-year period. For earnings below median, growth has been slower, between 35–44%, while above median the growth hovers around 53% to 60%, except for the very top where earnings grew by 75% and 110% for the top two groups, respectively.

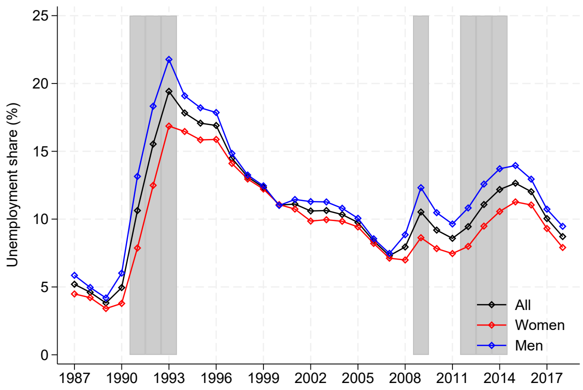
Figure 1: Macroeconomic and labor market performance in Finland



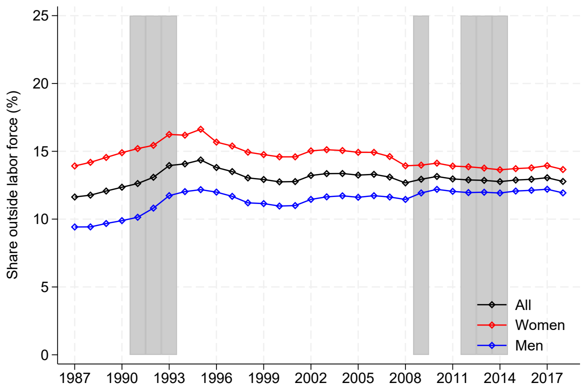
(a) Gross domestic product



(b) Employment share



(c) Unemployment share



(d) Outside of labor force

Note: Gross domestic product defined using a GDP volume index, normalized to year 1987. Employment share is defined as a share of population 25–55 years old, unemployment as a share of labor force of the same age. Share outside of labor force is defined as share outside per total population in the relevant age group. Shaded years represent recession years when GDP growth on annual level was negative. Source: Statistics Finland database (2024b, 2025).

2.2 Macroeconomic trends

We examine earnings inequality and volatility in Finland over a period of three decades, from 1987 to 2018. During this time, several major macroeconomic fluctuations have had a substantial impact on the evolution of earnings. Figure 1 summarizes Finland's macroeconomic and labor market performance for prime-age workers (25–55 years) during the observation period. Panel (a) depicts economic growth, measured by GDP normalized to its 1987 level. The shaded areas indicate recession years, defined here as annual negative GDP growth.[6] Particularly notable is the deep and prolonged recession of the early 1990s, which resulted from a combination of rapid financial liberalization, a stock market crash, a banking crisis, the collapse of trade with the Soviet Union–an important trading partner–and policy failures. The next sharp downturn was associated with the global financial crisis in 2009, followed by a brief rebound and then a period of sluggish growth. Between 2010 and 2018, annual GDP growth averaged 2%, compared with 5% per year during 1994–2008, including a spell of negative growth in 2012–2014.

Panel (b) shows the employment rate, which dropped sharply during the 1990s recession, coinciding with a steep increase in unemployment shown in panel (c). By contrast, the 2008 financial crisis had a much smaller effect on employment and unemployment compared to the 1990s recession. As in other Nordic countries, labor force participation rates are high for both women and men: among 25–55-year-olds, the employment rate was 78% for both genders in 2018. Panel (d) in Figure 1 illustrates that the share of women outside the labor force was relatively high in the early 1990s but has gradually converged toward the corresponding share for men over time.

2.3 Institutional context

Finland is a welfare state, where the public sector provides universal health care and old-age care, subsidized child care, free education, and generous social insurance benefits. Financing this system requires a relatively high tax burden: in 2022, Finland's tax-to-GDP ratio was 43%, compared to the OECD average of 34% (OECD database, 2025b). The tax and transfer system has also undergone several reforms during our observation period (see Paukkeri et al., 2023). Although our primary outcome is gross earnings, these policy changes may influence labor supply incentives and should be kept in mind when interpreting our results.

As our study examines the inequality and dynamics of labor earnings, the wage-setting system is central to the institutional context. Finland does not have a statutory minimum wage; instead, industry-level collective bargaining agreements (CBAs) set wage floors by occupation, task, and experience. Union membership is widespread, and because CBAs are automatically extended to sectors with at least 50% unionization, coverage is very high—averaging 88% during our study period (OECD/AIAS database, 2025). The wage negotiation system has undergone significant institutional changes over time. Before 2006, wage bargaining was characterized by tripartite, centralized agreements, in which the central employer and employee confederations negotiated jointly with the state (Kiander et al., 2011). During 1995–2000, these agreements included an increment for certain low-wage occupations that aimed at compressing the wage

[6] Throughout the paper, we use similar gray shading to indicate recession years, defined as negative annual GDP growth.

distribution. After 2006, the system has become more decentralized, though coordination persists through pattern bargaining, whereby key export sectors set benchmarks for other industries (Jonker-Hoffrén, 2019). Earlier research has documented that Finland's industry-specific minimum wages are relatively high by international standards (Böckerman et al., 2017). Also, the strong wage coordination is widely viewed as an important contributor to the comparatively low disposable-income inequality observed in Nordic countries relative to, for example, the UK and the US (Mogstad et al., 2025). The links between collective-bargaining institutions and inequality have also been analyzed in Kauhanen (2023) and Kauhanen et al. (2024).

3 Trends in earnings inequality and dynamics

3.1 Earnings Inequality

We start by presenting key findings on earnings inequality in Finland for years 1987–2018 based on the CS sample.[7]

Figure 2 shows changes in the log earnings distribution for both genders and selected percentiles, indexed to their 1987 levels.[8] Panels (a) and (b) make clear that the 1990s recession disproportionately affected the bottom of the distribution. Compared with Sweden (Friedrich et al., 2022), which also experienced a severe downturn, Finland saw a more pronounced earnings collapse: not only the bottom decile but the entire bottom quartile suffered substantial losses relative to 1987.[9]

This pattern is evident for both men and women. For men at the 10th percentile, earnings fell by 50 log points (nearly 65%) relative to 1987. The bottom of the distribution then experienced faster earnings growth than the middle and top during the recovery, up until the 2008 financial crisis. For women, earnings losses in the recession were smaller—around 25 log points (28%) at the 10th percentile. These gender differences likely reflect differences in industry exposure, as male-dominated manufacturing was hit particularly hard during the 1990s crisis (Verho, 2020). A similar pattern appears during the 2008 financial crisis: male-dominated industries bore the brunt of the downturn, and earnings declined at the bottom of the distribution for men but not for women. However, these changes were far milder than those observed in the 1990s. In contrast, median and upper-percentile earnings were only modestly affected by the recession and grew steadily until the financial crisis.

Panels (c) and (d) plot the evolution of log earnings within the top 10%. These panels show that the very top (99.9th percentile) has pulled away from the rest of the distribution, with substantial year-to-year variation. The sharp spike in panel (c) around 1999–2000 reflects the boom in Finland's technology sector and the widespread use of stock options during that period (Keloharju and Lehtinen, 2018). Because stock options are taxed as labor income when exercised, they are included in our earnings measure.[10] Women at the very top of the distribution (99.9th

[7] Additional results on earnings inequality can be found in the Appendix (Figures A.1–A.7).

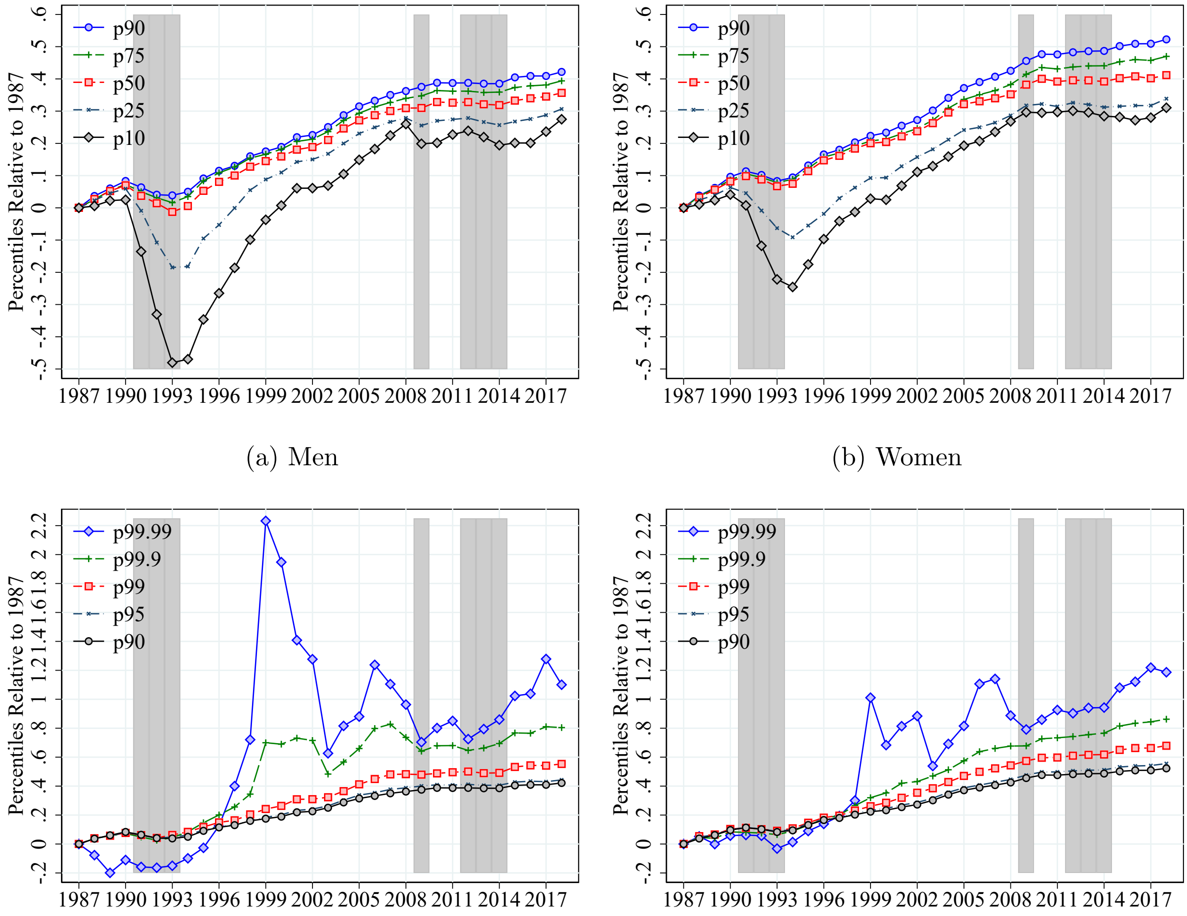
[8] We present results for men and women separately; Appendix Figure A.1 shows the same results for the full working-age sample. For changes in earnings shares, see Appendix Figure A.2.

[9] See Honkapohja (2009) for an overview of the 1990s recession in Finland and Sweden. He highlights the collapse of Soviet trade and various policy rigidities as key factors behind the deeper and more protracted recession in Finland relative to Sweden.

[10] Appendix Figures A.3 and A.4 control for changes in the age and education composition of earners to assess

percentile) also realized substantial income gains from stock options during the tech boom, albeit to a considerably lesser extent than men. We also examine the contribution of top incomes to inequality by fitting Pareto distributions to the upper tail, as shown in Appendix Figures A.5 and A.6. The Pareto slope parameters indicate that while top end inequality among men is always higher than women's, inequality among top women increased more between 1995 and 2015, as the upper tail has thickened more among women.

Figure 2: Change of Percentiles of the Log Real Earnings Distribution



(a) Men (b) Women

(c) Men (d) Women

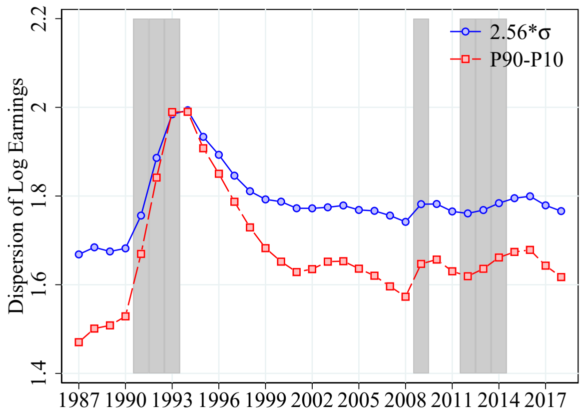
Note: Using raw log earnings and the CS sample, the Figure plots against time various percentiles of the earnings distribution for men and women. All percentiles are normalized to 0 in the first available year, 1987. Shaded areas indicate recessions.

Figure 3 summarizes overall earnings dispersion using two standard measures.[11] Panels (a) and (b) report $2.56 \times \sigma$ and the 90–10 percentile gap (P90–P10), which coincide under normality. Both measures show a sharp rise in dispersion during the 1990s recession for men and women alike. Although inequality gradually declined thereafter, dispersion remains permanently higher in the post-recession period than before. For men, the increase in dispersion during the 1990s recession is larger, and there is a noticeable—but much smaller—uptick during the 2008 financial

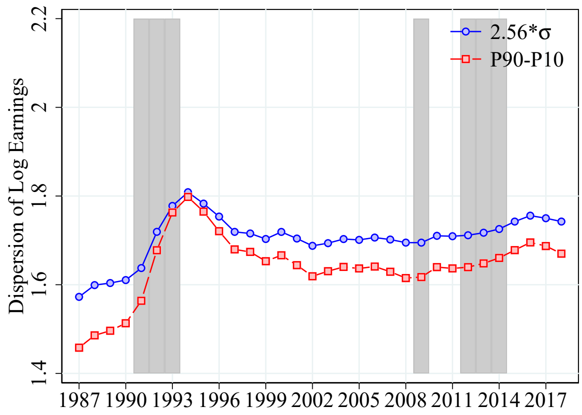
whether compositional shifts drive the patterns discussed above. With these controls, we find that earnings levels have diverged over time and that, outside the very top, there has been little earnings growth relative to 1987.

[11]Appendix Figure A.7 plots the Gini index for the working-age population.

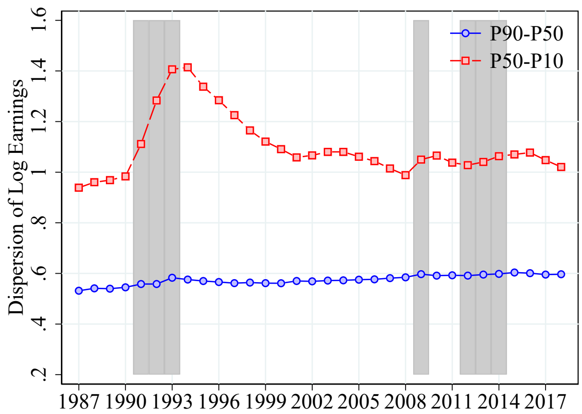
Figure 3: Income Inequality



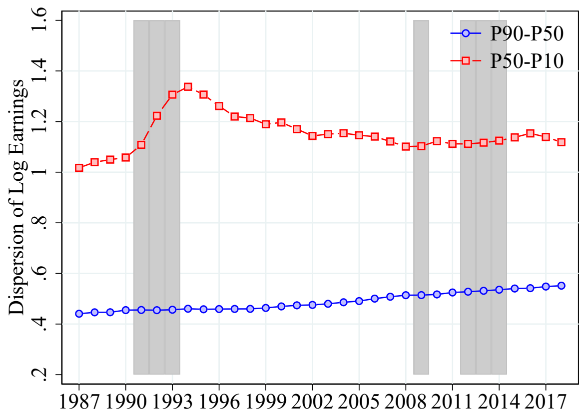
(a) Men



(b) Women



(c) Men



(d) Women

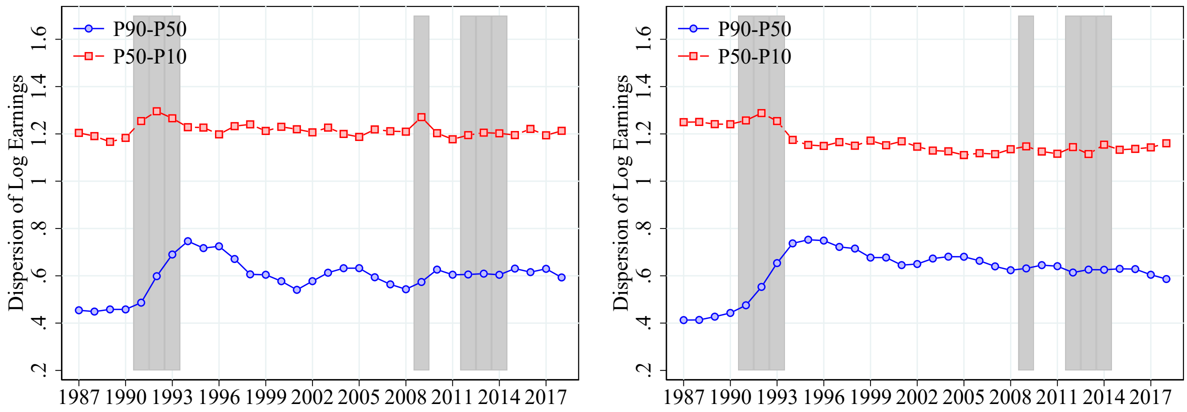
Note: Using raw log earnings and the CS sample, the Figure plots against time the P90–P10 differential and 2.56*SD of log income for men and women separately. 2.56*SD corresponds to P90–P10 differential for a Gaussian distribution. Shaded areas indicate recessions.

crisis. For women, the 2008 crisis had virtually no effect on log earnings dispersion. Outside recession periods, the levels of dispersion for men and women are very similar, in contrast to patterns documented in many other countries (Guvenen et al., 2022).

To unpack these patterns further, panels (c) and (d) decompose the P90–P10 gap into the distances between the 90th and 50th percentiles (P90–P50) and between the 50th and 10th percentiles (P50–P10). The 1990s recession predominantly affected the lower half of the distribution: P50–P10 widens sharply, while P90–P50 remains essentially flat. The lasting increase in post-recession dispersion is likewise driven entirely by the median pulling slightly away from the bottom decile. Similarly, the rise in dispersion during the 2008 financial crisis is concentrated among men in the lower part of the distribution, with no corresponding movement at the top.

Turning to workers who are just entering the labor market, the trends in inequality look quite different. Figure 4 plots the P90–P50 and P50–P10 gaps for individuals at age 25. In contrast to the overall population, the P90–P50 gap widens for these young workers during the

Figure 4: Income Inequality: Initial conditions

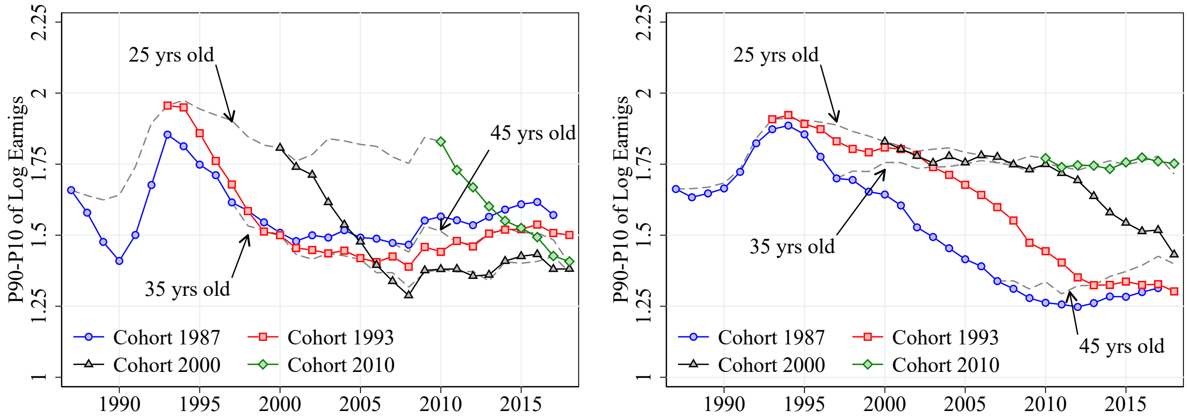


(a) Men (b) Women

Note: Using raw log earnings and the CS sample, the Figure plots against time the P90–P50 and P50–P10 differentials at age 25 for men and women separately. Shaded areas indicate recessions.

1990s recession, while the P50–P10 gap remains relatively stable. This pattern reflects that the crisis depressed earnings across a broader segment of the distribution for recent entrants: the median young man saw declines almost as large as those at the 10th percentile, whereas the median worker in the full population was much less affected. The results for young women closely mirror those for young men.

Figure 5: Life-Cycle Inequality over Cohorts



(a) Men (b) Women

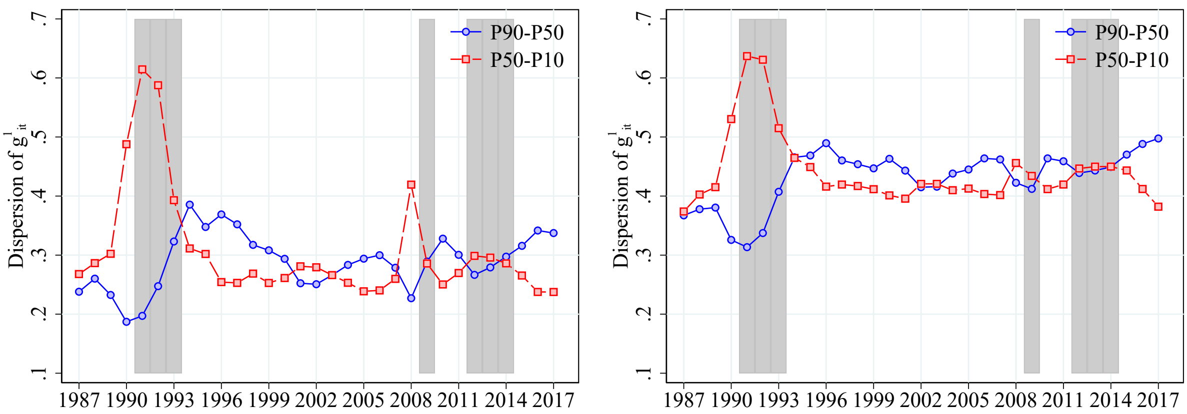
Note: Using raw log earnings and the CS sample, the Figure plots against time the P90–P10 differential over the life cycle for men and women separately. The solid lines correspond to outcomes of a given cohort at different ages, where the cohort labels indicate the year when the cohort is 25 years old. The dashed lines illustrate outcomes for 25-, 35- and 45-year-olds in different years, as indicated by the arrows.

Next we move from the cross-sectional analysis to tracking inequality over the life cycle for selected birth cohorts. Figure 5 shows that men's P90–P10 earnings dispersion is highest at age 25 and then decreases substantially with age. Women show a similar life-cycle pattern, although the contraction in dispersion is more gradual. This contrasts sharply with the United States and the United Kingdom, where earnings inequality tends to widen as workers age (Bell et al., 2022; McKinney et al., 2022). In Finland, roughly 15% of individuals in the CS sample are still registered as students at age 25, which contributes to the initially high dispersion, as many work part-time or only part of the year.[12] Among women, dispersion remains elevated between ages 25 and 30 before beginning to decline more noticeably at later ages. This likely reflects greater heterogeneity in hours worked during the childbearing years early in the life cycle.

3.2 Earnings dynamics

Earnings growth can also be examined through the panel structure of the LX sample, which allows us to trace earnings dynamics for the same individual over time. We use residualized log earnings growth rates to remove life-cycle and year influences. The main text focuses on one-year earnings changes, with Appendix Figures A.8–A.16 providing analogous results for five-year forward changes and related extensions.

Figure 6: Dispersion in 1-Year Log Earnings Changes



(a) Men (b) Women

Note: Using residual 1-year earnings changes and the LX sample, the Figure plots against time the P90–P50 and P50–P10 gaps for men and women separately. Shaded areas indicate recessions.

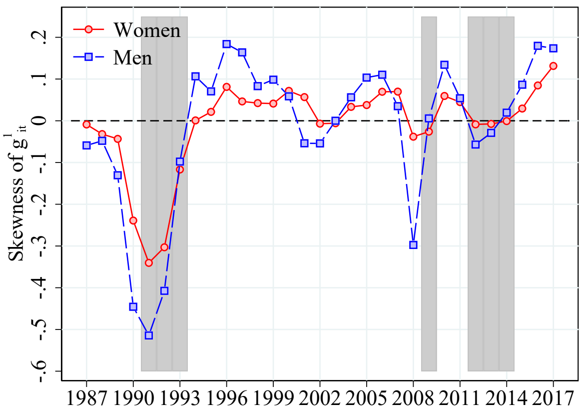
Volatility Figure 6 plots upper-tail (P90–P50) and lower-tail (P50–P10) differentials in one-year residualized log earnings growth rates. During the 1990s recession, the two measures diverged sharply for both women and men. Lower-tail dispersion widened as earnings losses deepened, while upper-tail dispersion narrowed as earnings gains diminished. Although Friedrich et al. (2022) document a similar pattern for Sweden, the spike in P50–P10 dispersion is substantially larger in Finland, indicating much more severe lower-tail earnings losses. This is consistent with Finland's dramatic rise in unemployment during the crisis, which far exceeded that in other Nordic countries. Even though our annual earnings measure incorporates a minimum threshold, the pronounced increase in lower-tail dispersion likely reflects a sharp fall in months worked. Because unemployment dynamics play a central role in shaping inequality during the 1990s crisis,

[12]Friedrich et al. (2022) document a similar life-cycle profile, with the reduction in inequality over age driven largely by shrinking dispersion in annual hours worked.

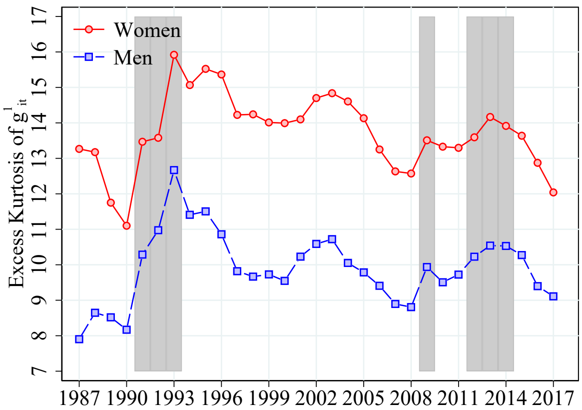
we analyze them separately in Sections 4.1 and 4.2, where we explicitly allow non-employment to enter the distribution.

A similar pattern—a spike in the P50–P10 gap and a decline in the P90–P50 gap—also appears during the 2008 financial crisis particularly among men, though the magnitudes are much smaller than in the 1990s. Between the recession episodes, during periods of recovery and stable economic growth, dispersion in earnings changes returns close to pre-1990s levels for men but remains elevated for women. In general, there is a persistent gender gap in earnings volatility: women experience larger earnings fluctuations, likely due to greater variability in labor supply associated with care-taking responsibilities and more frequent transitions between full- and part-time work.

Figure 7: Skewness and Kurtosis of 1-Year Log Earnings Changes



(a) Skewness



(b) Excess Kurtosis

Note: Using residual 1-year earnings changes and the LX sample, the Figure plots against time the Kelley skewness, defined as $\frac{(P90-P50)-(P50-P10)}{P90-P10}$, and excess Crow–Siddiqui kurtosis, defined as $\frac{P97.5-P2.5}{P75-P25}-2.91$, for men and women separately. A normal distribution has Kelley Skewness equal to zero and Crow-Siddiqui kurtosis equal to 2.91. Shaded areas indicate recessions.

Skewness We examine the higher-order moments of the earnings growth distribution using percentile-based measures.[13] Using the distribution of residualized 1-year log income changes, we define skewness as (Kelley's skewness):

$$\frac{(P90-P50)-(P50-P10)}{P90-P10}.$$

This skewness measure has an intuitive interpretation: it captures the difference between upper-tail and lower-tail dispersion in earnings changes as a share of overall dispersion (excluding the top and bottom 10%). Negative values—indicating that the P50–P10 gap exceeds the P90–P50 gap—signal that lower-tail outcomes contribute more to total dispersion (left-skewness). Positive values imply the opposite (right-skewness).

Figure 7 panel (a) shows that skewness in the residual log earnings growth distribution is

[13]For standardized moments, see Appendix Figures A.15 and A.16. The percentile-based measures are less sensitive to outliers than the standardized moments.

strongly correlated with the business cycle: it turns negative in recessions and positive during periods of economic expansion. Two additional observations are worth noting. First, during the 1990s recession, Finland's Kelley skewness drops to a level markedly lower than in nearly all comparison countries reported in Guvenen et al. (2022).[14] This further underscores the severity of the crisis in Finland and the surge in lower-tail earnings volatility. Second, changes in skewness over time are more pronounced for men than for women. This likely reflects sectoral composition: women are more concentrated in the public sector (Statistics Finland database, 2024a), where earnings losses tend to be less severe during recessions, but earnings gains are also more modest during economic expansions.

Kurtosis To measure the extent of extreme income changes at the tails of the distribution, we compute the Crow-Siddiqui kurtosis, defined as:

$$\frac{P97.5 - P2.5}{P75 - P25}.$$

Figure 7 panel (b) shows that tail events in earnings growth increased for both men and women during the 1990s recession. Combined with the pronounced left-skewness, this indicates that a substantial share of the workforce experienced large earnings losses and elevated downside volatility during the severe crisis. The persistently higher kurtosis for women suggests that female workers faced greater exposure to extreme earnings changes—such as temporary exits from the labor market. Although excess kurtosis gradually declined from its peak in the 1990s crisis, the gender gap in this measure has remained persistent.

Life-cycle dynamics We can further explore the distributions of one-year earnings changes over the life-cycle and across the income distribution. Using the H sample, Figure 8 plots the P90–P10 gap, the Kelley skewness and the excess Crow–Siddiqui kurtosis of one-year earnings changes by age group as a function of permanent earnings.

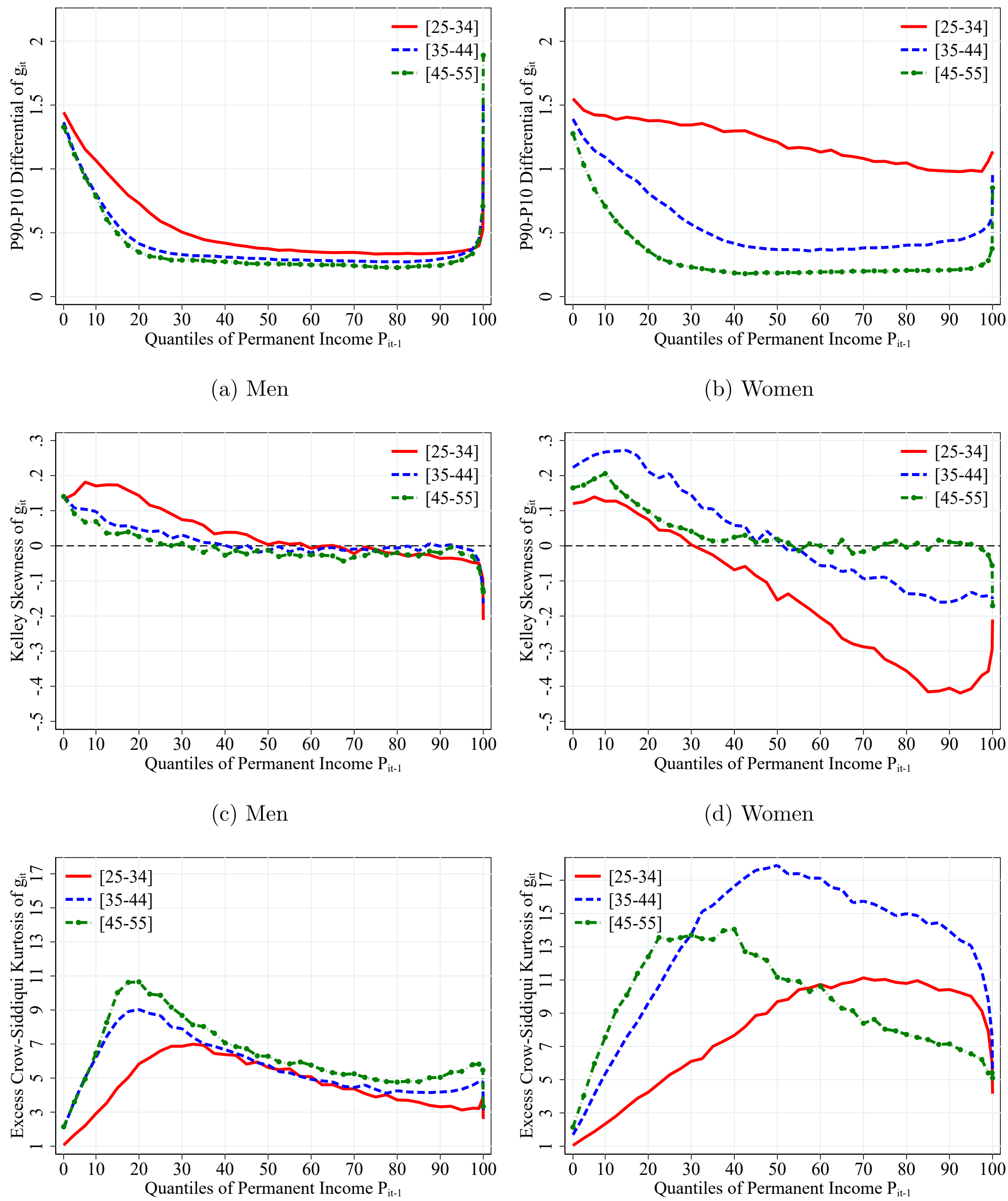
Panels (a) and (b) show that earnings volatility follows a U-shaped pattern across the permanent income distribution: workers at the top 5% and bottom 20% of the distribution experience more dispersed earnings changes. This pattern holds for both men and women across all age groups, with one exception—women aged 25–34. For women in this child-rearing age range, earnings volatility is high throughout the permanent income distribution, likely reflecting the widespread use of parental leave among Finnish women. Women's earnings volatility declines substantially over the life cycle and converges to that of men by ages 45–55. This suggests that gender differences in volatility are driven largely by life-cycle timing and family-related labor supply adjustments.[15]

Panels (c) and (d) reveal pronounced gender differences in the skewness of earnings changes over the life cycle. For men, skewness is near zero across most of the permanent income distribution, turning negative only for the richest 5%. In contrast, women aged 25–44 display a steep decline in Kelley skewness from the bottom to the top of the permanent income distribution.

[14] Kelley skewness for Spanish men reaches –0.5 during the 2008 Financial Crisis, but no other country gets close to Finland's 1990s level (-0.5 for men and -0.35 for women).

[15] Guirola et al. (2024) show that the employment and earnings gap between mothers and fathers narrows between ages 30 and 50 in many countries, and more sharply in Finland.

Figure 8: Dispersion, Skewness and Kurtosis of 1-Year Log Earnings Changes



(a) Men

(b) Women

(c) Men

(d) Women

(e) Men

(f) Women

Note: Using residual 1-year earnings changes and the H sample, the Figure plots against permanent income quantile groups the following variables for the three age groups, for men and women separately: P90–P10, Kelley skewness, and Crow-Siddiqui kurtosis. Kelley skewness is defined as $\frac{(P90-P50)-(P50-P10)}{P90-P10}$. Excess Crow–Siddiqui kurtosis is defined as $\frac{P97.5-P2.5}{P75-P25} - 2.91$. A normal distribution has Kelley Skewness equal to zero and Crow-Siddiqui kurtosis equal to 2.91. The Figure presents average outcomes across the years during 1999–2013.

Earnings changes are left-skewed for all women in these age groups with above-median permanent income, with high-income women experiencing the most negative shifts. This negative skewness is consistent with sizable downward earnings movements associated with parental leave and reductions in labor supply. At the bottom of the distribution, however, positive skewness among both young men and women suggests different mechanisms: for young men, positive shocks may reflect upward mobility, while for women—particularly those aged 35–44—stronger positive skewness likely reflects increasing labor market attachment.

Panels (e) and (f) show that kurtosis follows a hump-shaped profile over the permanent income distribution, with women exhibiting a higher peak than men in all age groups. For men, extreme earnings changes are most common in the bottom quartile, and the Crow–Siddiqui measure declines steadily with income, indicating increasingly stable earnings among higher earners. In contrast, for women aged 25–44, large tail events are even more frequent above the median of the permanent income distribution. Kurtosis reaches its highest levels for women aged 35–44, consistent with this group experiencing both substantial labor supply declines and increases.

Notice that the permanent earnings quantiles in Figure 8 are more disaggregated at the top: we show average outcomes for P99, P99.9 and the top. The income rank trends are often different at the very top.

3.3 Earnings mobility

Intragenerational mobility is a central dimension of income inequality and income dynamics. Higher mobility implies that cross-sectional inequality in annual earnings might overstate inequality in life-cycle earnings. To study this, we construct an average rank–rank mobility measure that captures an individual's expected position in the income distribution in year $t + k$, conditional on their position in year t. To incorporate workers with weaker labor market attachment, we use a modified measure of permanent income that includes earnings below the minimum earnings threshold in at most two years between years $t - 2$ to t. In this section, we report average rank–rank mobility between years t and $t + 10$.[16]

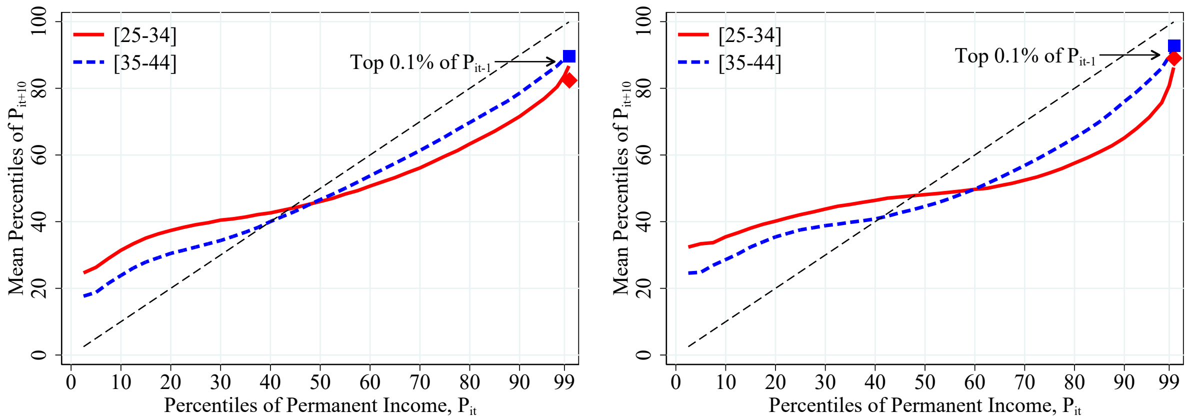
Figure 9 plots average rank–rank mobility by age group and gender, and several patterns emerge. First, income mobility declines markedly over the life-cycle for both men and women, consistent with evidence from other countries showing that income becomes more persistent as careers progress.[17] Second, women with low permanent income exhibit greater upward mobility than men, likely reflecting differences in early career trajectories, as women often begin at lower earnings levels due to later labor market entry or part-time work around family formation. Third, at the top of the distribution, women display somewhat greater downward mobility than men, consistent with their more limited representation in high-wage, high-growth occupations such as managerial roles in ICT and finance.

Appendix Figure A.18 further shows that ten-year mobility remained remarkably stable between 1995 and 2005. Taken together, these findings indicate that Finland's earnings mobility remained high even as annual earnings inequality increased after the 1990s crisis.

[16] Results for five-year mobility are shown in Appendix Figure A.17.

[17] The same pattern is observed in Sweden (Friedrich et al., 2022), Norway (Halvorsen et al., 2022), Denmark (Leth-Petersen and Sæverud, 2022), the UK (Bell et al., 2022), and the US (McKinney et al., 2022).

Figure 9: Evolution of 10-Year Mobility Over the Life Cycle



(a) Men (b) Women

Note: The Figure shows average rank-rank mobility over 10 years by computing average percentiles of permanent income 10 years later for workers in each permanent income percentile in the base year, for men and women and age groups separately, and taking the average across all years in the data.

4 Inequality across regions and industries

Section 3.1 documented an overall increase in income inequality in Finland following the recovery from the 1990s economic crisis. A key question is whether this rise occurred uniformly across the country or whether regions diverged, with poorer areas falling further behind. Regional divergence could arise because the collapse of trade with the Soviet Union disproportionately affected some parts of the country (Costinot et al., 2024), while a nationwide banking and currency crisis (Gulan et al., 2021) likely shaped inequality within regions as well. Between 1987 and 2018, economic expansions and contractions could have had uneven effects across regions, reflecting differences in sectoral composition. This section documents these industrial differences across regions and examines how they have shaped the divergent trajectories of regional inequality.

To examine how inequality evolved across space, we classify Finnish municipalities into three region types: the capital region, other cities, and small towns and rural areas.[18] To study the evolution of industries consistently over the full sample period, we group industry codes into 15 broad categories that remain comparable across time.[19] Industry codes are observed only for individuals employed in the last week of the calendar year, so the industry sample is slightly smaller. Nevertheless, the main qualitative trends (see Figure B.3) across regions remain consistent with those in the full sample presented next.[20]

[18]The capital region includes Helsinki and its surrounding municipalities Espoo, Vantaa and Kauniainen. "Other cities" comprise of municipalities where above 90% of the population lives in urban areas, or that contain an urban area of at least 15,000 inhabitants. "Small towns and rural areas" cover the remaining sparsely populated municipalities. See a map of the classification in Figure B.1. As shown in Figure B.2, the Helsinki region accounted for 20–25% of the sample population during the sample period, other cities for about 50%, and rural areas for 25–30%.

[19]Industry classifications changed several times during the three decades covered in our data. We harmonized the definitions wherever possible to obtain a consistent set of industry groups over time.

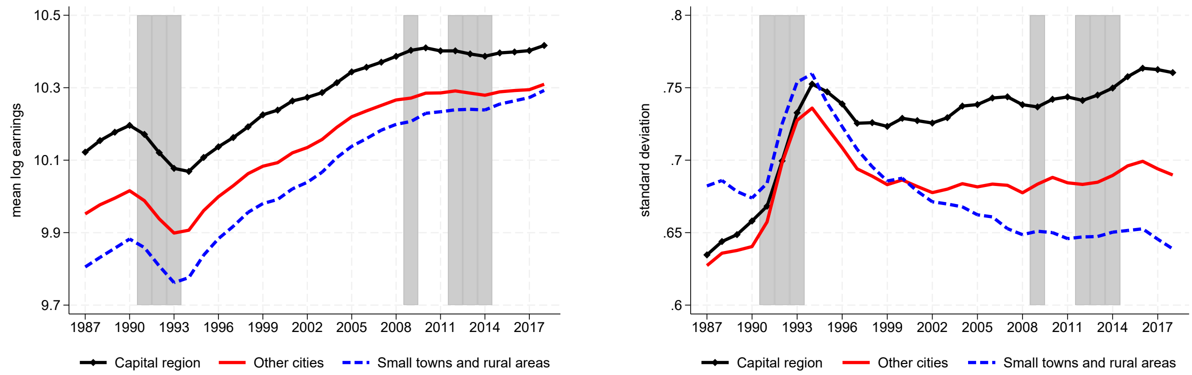
[20]This restriction may exclude some individuals who were employed earlier in the year, thereby omitting part of the annual earnings variation. Reassuringly, while the overall level of variance is lower, the regional and temporal

4.1 Between- vs. within-region inequality

We start by examining how average earnings and earnings dispersion compare across the three regions over time. We find that the post-crisis increase in overall inequality was driven mainly by rising within-region disparities. Perhaps counterintuitively, the three regions converged in mean log earnings rather than diverged.

The decline in between-region inequality is evident in Figure 10a. In 1987, mean earnings in rural areas were well below those in Helsinki, but all regions suffered sharp losses during the 1990s crisis before beginning to converge thereafter. Faster post-crisis income growth in rural areas narrowed much of the gap with Helsinki and other cities. This convergence pattern remains robust to alternative income measures. By using the inverse hyperbolic sine transformation instead of log earnings, we do not have to drop zero incomes and can hence account for the effect of non-employment on mean earnings.[21] This is done in Figure B.4a, which this way illustrates less earnings growth in Helsinki and other cities in the 2000s, but with clear convergence across regions over the time period. Additionally, by residualizing log earnings by age and gender similarly as done in Section 3.2 we show that mean earnings converge across regions even when accounting for differences in gender and age between the regions (Figure B.4b).

Figure 10: Comparison of convergence patterns across regions



(a) Mean log earnings

(b) Standard deviation of log earnings

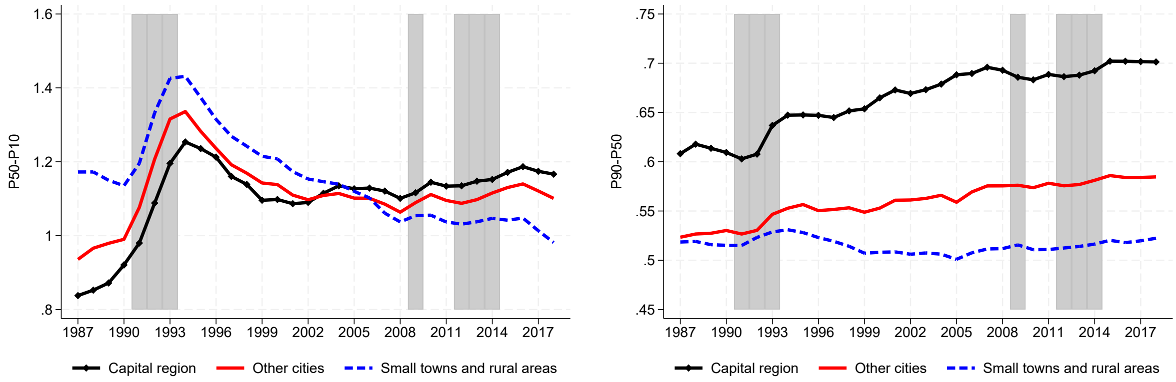
Note: The Figure shows the mean and standard deviation of log real annual earnings across time by region. Sample includes 25–55-year old individuals with income above the minimum annual earnings threshold (CS sample). Shaded areas indicate recessions.

In contrast, within-region inequality followed a different trajectory. As shown in Figure 10b, all regions experienced a surge in income dispersion during the early 1990s, followed by partial recovery in the late 1990s. However, dispersion in the capital region remained persistently high, while inequality in rural areas continued to decline, eventually reaching levels below those observed before the crisis. Since Helsinki and other cities account for over 70 percent of the Finnish population, the sustained rise in their within-region inequality contributed substantially to the persistence of overall earnings inequality in Finland observed in Section 3.

trends are very similar to those in the main sample.

[21] The inverse hyperbolic sine conversion is defined as $asinh(y) = ln(y + \sqrt{y^2+1})$. Unlike the logarithm, it is defined for zero and negative values of y, and for large values of y, it is approximately equal to $ln(y) + ln(2)$, and can hence be interpreted similarly to a natural logarithm (Norton, 2022).

Figure 11: Bottom and top inequality by region type



(a) P50–P10

(b) P90–50

Note: The Figure shows the P50–P10 and P90–P50 differentials in log earnings across time by region. Sample includes 25–55-year old individuals with income above the minimum annual earnings threshold (CS sample). Shaded areas indicate recessions.

To shed light on the divergent trends of income dispersion between urban and rural regions, we examine the evolution of incomes at the bottom and top of the distribution by region. As shown in Figure 11, the decline in overall inequality in rural areas is largely driven by falling bottom inequality (P50–P10). Figure B.5 clarifies the trends in P10, P50 and P90 separately. Both rural regions and “other cities” experienced strong growth in P10 incomes following the 1990s crisis. In contrast, the rise in inequality in the capital region was fueled by widening top inequality (P90–P50), while its bottom incomes stagnated. P10 earnings in Helsinki recovered to pre-crisis levels only after 2008 and have remained flat since, whereas those in rural areas and other cities rebounded much earlier, in the late 1990s and early 2000s, respectively.

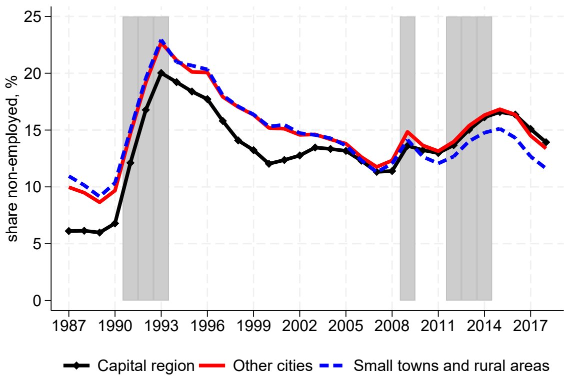
A possible explanation for these divergent patterns is selective migration across regions. If lower-income workers from rural areas moved to larger cities in search of better opportunities, such movements could raise lower-tail inequality in urban areas while compressing it in rural regions. In practice, however, migration appears too limited to fully account for the observed shifts in bottom incomes (Figure B.9). The five-year migration rate from rural regions to Helsinki is only about 1%, with no noticeable change after the 1990s crisis. Migration from other cities to Helsinki rises slowly from around 2% in 1987 to about 3% in the 2010s, but this gradual trend is unlikely to explain the sharp increase in income inequality in Helsinki. It is also notable that in-migration into rural areas from “other cities” rose from about 6% of the rural population in the late 1990s to 10% in the late 2000s. However, even this level of migration is likely to have a limited effect on bottom incomes in rural areas.

Another potential mechanism behind the observed trends is immigration to Finland from abroad. Even though immigration is a relatively small phenomenon in Finland compared to many other European countries, the population share of non-native background has increased considerably during the time period we study and concentrated to capital region, where the share of 25–55-year-olds with a foreign background has risen from 2% in 1987 to 22% in 2018. In contrast, this change was from under 1% to 10% in other cities and to 6% in rural areas. To understand better whether non-natives are driving some of the observed patterns, we run the same analysis for people with native background only and observe that the trends in regional inequalities are virtually unchanged.

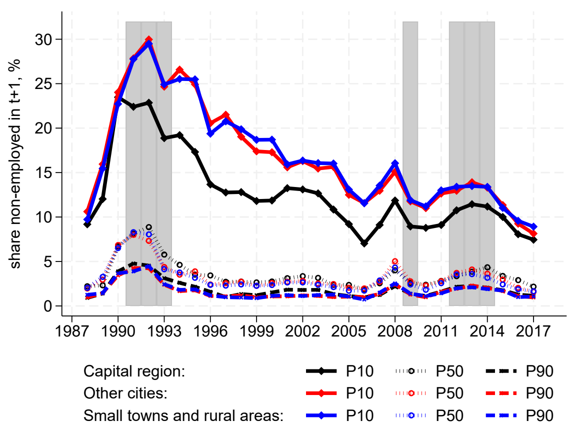
4.2 Non-employment across regions

Bottom incomes are closely tied to non-employment. Understanding the evolution of earnings distributions therefore requires examining the experiences of workers outside employment, particularly during and after the 1990s crisis. For example, recessions can increase non-participation, which in turn can be very persistent and hence have lasting effects on earnings inequality (Heathcote et al., 2020).

Figure 12: Non-employment and unemployment transition rates across regions



(a) Non-employment rate



(b) Transition rate to unemployment by rank

Note: Panel (a) shows the proportion of the population aged 25–55 years who are non-employed (defined as unemployed + out of the labor force). Panel (b) shows the proportion of 25–55-year-olds who are non-employed at the end of year $t+1$, as a share of the population with annual earnings above the minimum threshold and employed at end of the year in year t (horizontal axis), and located at a given permanent income rank in year t. Permanent earnings P_{is} for an individual in year s are obtained by first calculating average earnings in years s, $s-1$ and $s-2$, then residualizing these log average earnings on age and gender for each year s. To be assigned a permanent earnings measure for year s, the individual can have income below the minimum earnings threshold at most in one year of the three years used in the calculation. Individuals are ranked annually according to their permanent income at the national level. Shaded areas indicate recessions.

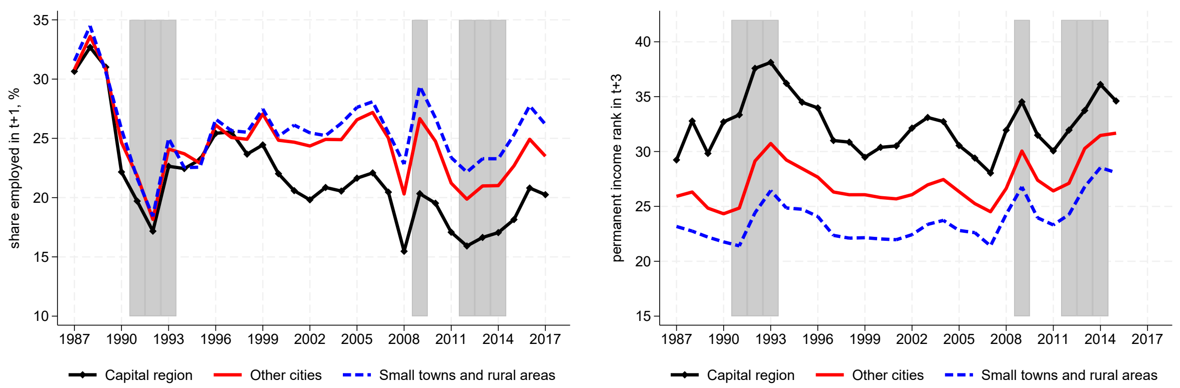
We define non-employment as being registered as an unemployed job seeker or being out of the labor force in the last week of the calendar year.[22] During the crisis of the early 1990s, non-employment rose sharply across all regions. As shown in Figure 12a, rural areas and other cities started with higher baseline rates (around 10%) in 1980s, which surged to about 23% at the peak of the economic downturn in 1993, compared with an increase from 6% to 20% in the capital region. Although nonemployment gradually declined thereafter, it has remained persistently above pre-crisis levels, hovering around 13% in all regions even to this day. Notice also that the shorter-lived effect of the financial crisis in 2009 is similar in each region.

[22]This definition captures discouraged workers displaced during the crisis. Full-time students, military service draftees, and pensioners are not defined as non-employed.

Those at the bottom of the income distribution are particularly vulnerable to unemployment shocks. As shown in Figure 12b, individuals at the national P10 earnings rank faced a much higher probability of moving from employment to unemployment. At the height of the crisis, 20–30 percent of them entered unemployment within a year, compared with 5–10 percent among median earners and about 5 percent among those at P90. Regional differences are also pronounced. Conditional on earning the same national P10 income, workers in ”other cities” and rural areas were 5–8 percentage points more likely to lose their jobs than those in Helsinki throughout the period.

Unemployment is a function of both how many people lose their jobs and how many find new jobs when unemployed. Figure 13 illustrates how the job finding rate was very similar across regions at the beginning of the period but diverged since the 2000s as job finding became less likely in the capital region. Nevertheless, unemployed workers who find jobs consistently end up higher in the income distribution in the Helsinki region throughout the period.

Figure 13: Job finding rate and earnings after finding a job, across regions



(a) Job finding rate

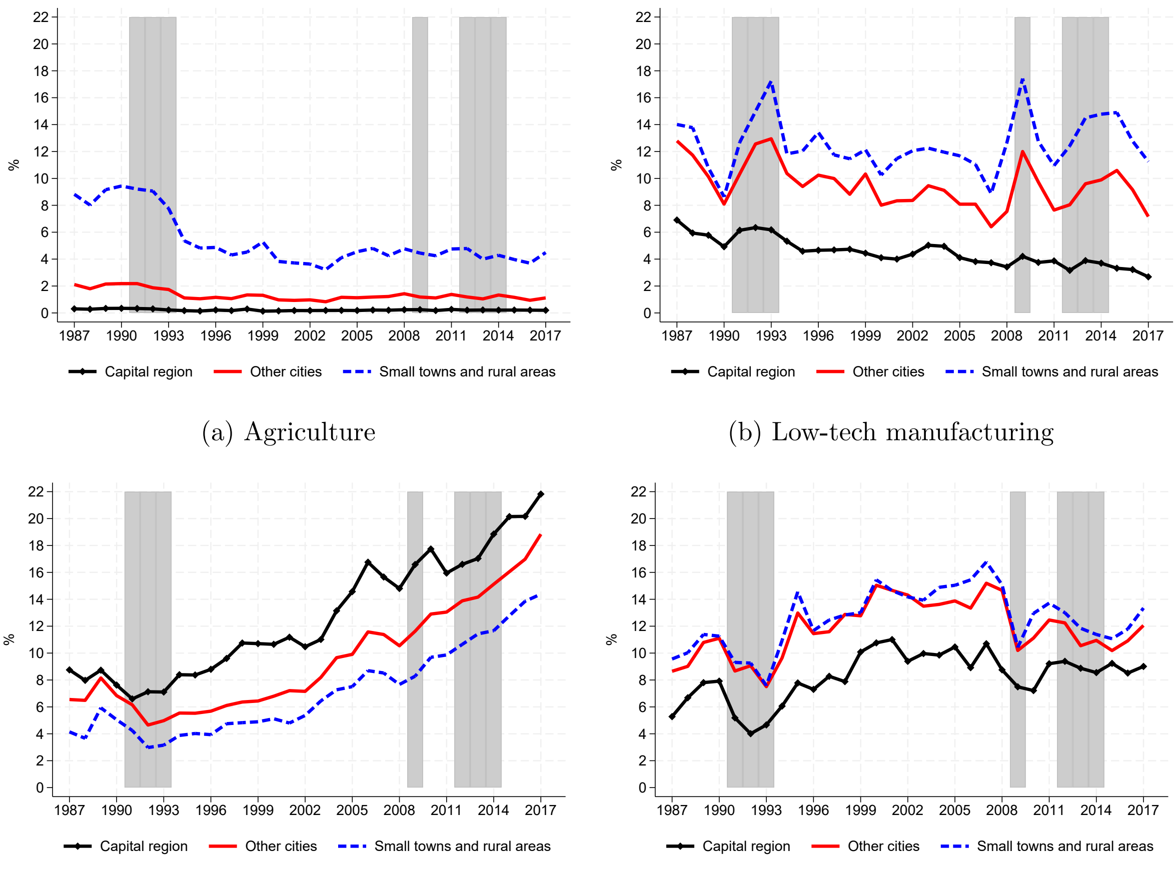
(b) Mean permanent income rank after finding a job

Note: Panel (a) shows the proportion of the population aged 25–55 years who are non-employed (defined as unemployed + out of the labor force) at the end of year t (horizontal axis) and employed at the end of $t+1$ with annual income above the minimum threshold. Panel (b) shows the mean permanent income rank in year $t+3$ conditional on having been unemployed at the end of year t (horizontal axis) and employed in $t+1$ (and conditional on having a permanent income measure in $t+3$). Permanent earnings P_{is} for an individual in year s are obtained by first calculating average earnings in years s, $s-1$ and $s-2$, then residualizing these log average earnings on age and gender for each year s. To be assigned a permanent earnings measure for year s, the individual can have income below the minimum earnings threshold at most in one year of the three years used in the calculation. Individuals are ranked annually according to their permanent income at the national level. Note that unemployment in t does not affect permanent earnings measure in $t+3$. Unemployed individuals in year $t+3$ are given a rank zero. Shaded areas indicate recessions.

Whereas immigration flows did not have much effect on the overall earnings trends across regions in the previous subsection, part of the differences in unemployment and job finding can be traced back to increases in the population share of non-natives. Natives fare better in terms of employment, as the gap in job finding is up to 5 percentage points smaller in the latter part of the period, and the mean rank to which they position after employment is up to 5 ranks higher (Figures B.7–B.8).

Re-employment after job loss also shows considerable regional differences in the industries that absorb displaced workers. As shown in Figure 14, while low tech manufacturing and

Figure 14: Job finding rates across regions over time, selected industries



(a) Agriculture

(b) Low-tech manufacturing

(c) Low-skilled services

(d) Social services

Note: Sample is 25–55 years old and unemployed in year t (x-axis) and employed in $t+1$. Graph illustrates the share of these workers who find employment in the given industry, calculated for each region separately. Shaded areas indicate recessions.

social services are important for unemployed workers in rural areas and small cities, low-skill services have grown in importance in all regions, especially in Helsinki. Because individuals who recently exit unemployment are typically concentrated at the lower end of the earnings distribution, the performance of these industries plays a key role in shaping the evolution of P10 incomes. Consequently, changes in both between- and within-sector inequality have important implications for the dynamics of inequality across regions, as discussed in the next section.

4.3 Structural changes in regional economies

An important factor behind the divergent regional patterns of inequality is the profound sectoral transformation throughout the sample period, with gradual shifts in employment across low-skilled and technology-intensive industries. Because regions differ markedly in their industrial composition, these structural shifts likely had heterogeneous effects on local labor markets and inequality.[23]

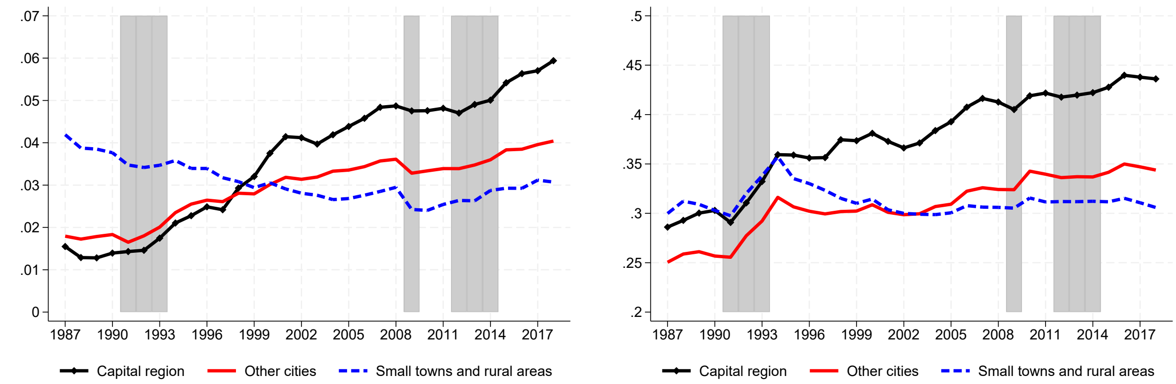
[23] Using plant closures during the 1990s recession as exogenous variation, Verho (2020) has shown that job loss during the crisis reduced earnings by 5-8% over 10 year period for men, and manufacturing and residing in more rural areas drives this effect.

To quantify how industrial transformation shaped the evolution of regional inequality, we decompose the change in earnings variance within each region into between- and within-industry components. This exercise allows us to assess whether the divergence in inequality across regions primarily reflects structural transformation—workers reallocating across sectors with different pay levels—or increasing dispersion among workers employed in the same sector.

All exercises are conducted at the regional level, so we omit the regional subscript for simplicity. Let y_{ik} denote the income of individual i in industry $k = 1, 2, ..., K$. Suppose N^k is the number of workers in k. The overall mean income in the region can be written as: $\overline{\overline{y}} = \frac{1}{N}\sum_k^K N^k\,\overline{y}^k$, where $\overline{y}^k$ is the mean income in industry k and $N = \sum_k N^k$ is the total number of workers in the region. Simple algebra shows that the overall variance in earnings can be decomposed as follows:

$$\frac{1}{N}\sum_k^K \sum_{i=1}^{N^k} (y_{ik} - \overline{\overline{y}})^2 = \underbrace{\frac{1}{N}\sum_k^K \sum_{i=1}^{N^k} (y_{ik} - \overline{y}^k)^2}_{\text{within-variation}} + \underbrace{\sum_k^K \frac{N^k}{N} (\overline{y}^k - \overline{\overline{y}})^2}_{\text{between-variation}} \tag{1}$$

Figure 15: Variance decomposition into within and between industry variance



(a) Between-variance (b) Within-variance

Note: The Figure shows the between- and within industry variance (see Eq. (1)) over time and across regions using the population 25–55 years old with income above the minimum threshold and nonmissing industry info (industry sample) using 15 industry groupings. Shaded areas indicate recessions.

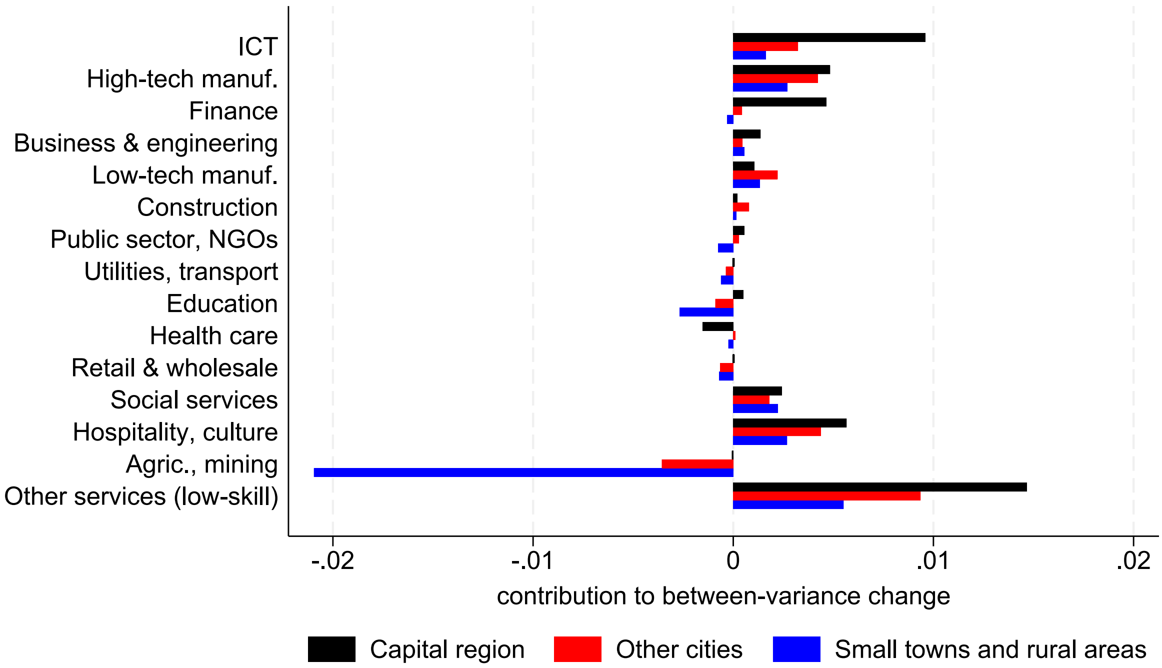
Figure 15 shows that at any given point in time, the within-industry variance accounts for a much larger share of overall inequality than the between-industry component in all three regions.[24] The evolution of these components over time, however, differs markedly across space. In Helsinki and other cities, both within- and between-industry inequality have risen substantially over time, whereas in small towns and rural areas, the within component has remained broadly stable (aside from the 1990s crisis years) and the between component has declined.

Comparing Equation (1) at two points in time (1987 and 2018)[25], the *change* in overall

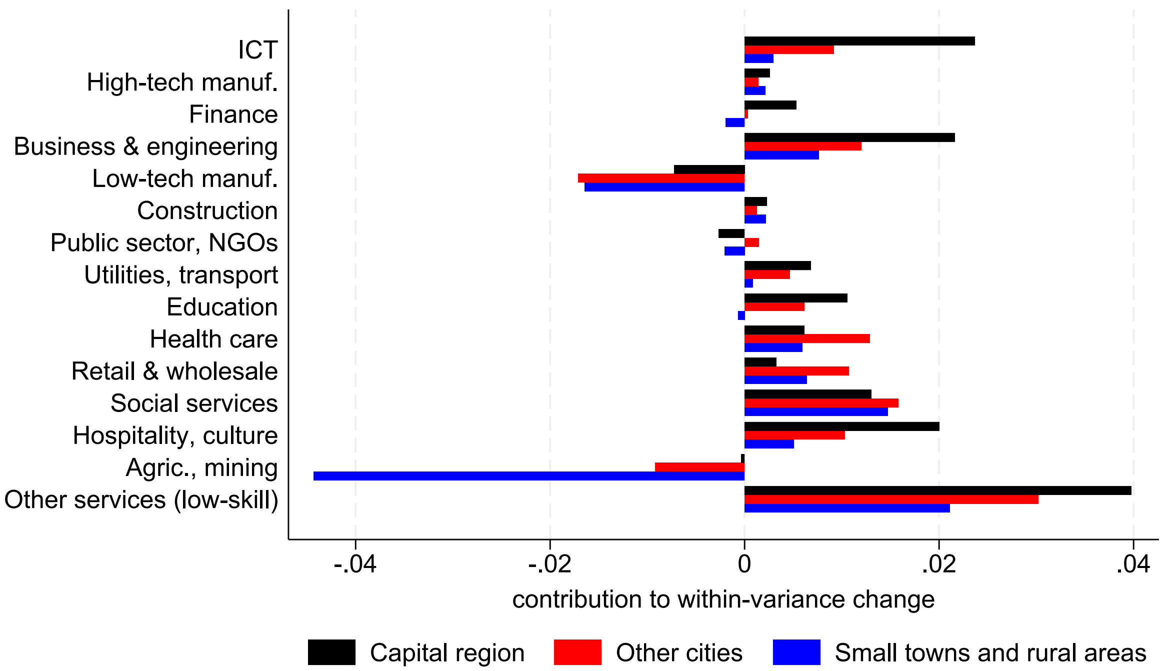
[24] Table B.2 shows that 88 to 95 percent of total inequality within a region can be attributed to within-industry variance. This contrasts with evidence from the United States, where differences between industries and their growth over time play a much larger role (Haltiwanger et al., 2024).

[25] We use the average in 1987–1989 and in 2016–2018.

Figure 16: Contribution of industries to within and between-industry variance change across regions



(a) Industry contributions to between-industry variance growth: $\Delta\left(\frac{N^k}{N}\left(\overline{y}^k - \overline{\overline{y}}\right)^2\right)$



(b) Industry contributions to within-industry variance growth: $\Delta\left(\frac{N^k}{N}\,\mathrm{Var}(y_{ik}|i \in k)\right)$

Note: The Figure illustrates each industry's contribution to the growth in between and within industry variance (see Equations (2) and (3)) in each region. Sample is the population 25–55 years old with income above the minimum threshold and nonmissing industry info (industry sample), using 15 industry groupings. Industries are sorted in descending order of national mean industry earnings in 2018. The shorthands used are explained in Table B.1.

inequality can be expressed as the sum of changes in the between- and within- industry components:

$$\text{between-industry variance change} = \sum_{k=1}^{K} \Delta \underbrace{\left(\frac{N^k}{N}\right)}_{\substack{\text{industry } k\text{'s} \\ \text{employment share}}} \underbrace{\left(\overline{y}^k - \overline{\overline{y}}\right)^2}_{\substack{\text{industry } k\text{'s} \\ \text{relative earnings}}} \tag{2}$$

$$\text{within-industry variance change} = \sum_{k=1}^{K} \Delta \underbrace{\left(\frac{N^k}{N}\right)}_{\substack{\text{industry } k\text{'s} \\ \text{employment share}}} \underbrace{\text{Var}(y_{ik}|i \in k)}_{\substack{\text{earnings variance} \\ \text{within industry k}}} \tag{3}$$

Conceptually, industries can influence regional inequality through four channels, or a combination of them. A decline in earnings inequality, for instance, may result from:
(i) faster wage growth in low-paying sectors relative to high-paying ones, holding employment shares constant;
(ii) shifts in employment from the top or bottom of the wage distribution toward middle-paying industries, holding sectoral wages constant;
(iii) reduced within-industry dispersion, even when both sectoral wages and employment shares remain unchanged; or
(iv) shifts in employment from high-variance to low-variance industries.

Channels (i) and (ii) correspond to changes in between-industry variance in Equation (2), whereas (iii) and (iv) relate to changes in within-industry variance in Equation (3). Conversely, the reverse mechanisms generate an increase in inequality.

Figure 16 shows the contribution of each industry to the changes in between- and within-industry inequality between 1987 and 2018 in each region. A positive bar indicates that the industry increased inequality in the region, while a negative bar indicates a decrease in inequality. The sum of the bars within a region equals the total change in the corresponding variance component.

In the Helsinki region for example, between- and within-variance increased by 0.044 and 0.145, respectively (Table B.2 shows a detailed breakdown). The largest contributions come from both ends of the earnings distribution. High-paying industries such as ICT, business services, and engineering, as well as low-paying industries such as low-skill services and hospitality, all contributed to the rise in overall inequality in the capital region.

Figure 17 further breaks down the components of the change in the between-variance. As shown in Figure 17a, the ICT sector expanded rapidly over time, especially in the greater Helsinki area. Rising mean earnings and growing within-industry dispersion in ICT boosted both the between- and within-components, fueling top income growth in the capital region. At the lower end of the income distribution, employment in low-skilled services grew considerably, but wages in this sector lagged behind the regional average (Figure 17b). This low-paid sector, which includes jobs in outsourced services, security services, cleaning and laundry, absorbed a growing share of unemployed workers—from about 8 percent in the early 1990s to 22 percent in 2018 in Helsinki (Figure 14). The lack of wage growth in this sector likely explains the sluggish recovery of the P10 income in Helsinki shown in Figure B.5. Changes in the low-skill service sector alone raised Helsinki's between-industry variance by 0.015 and its within-variance by 0.04.

In contrast, rural areas experienced a decline in the between-component (–0.01) and little change in the within-component. The small overall change masks substantial heterogeneity across industries: some sectors evolved in ways that increased inequality, while others helped to reduce it, resulting in an almost offsetting net effect.

Agriculture and low-tech manufacturing saw the largest employment contractions (Figure 17a) especially in rural areas, while wages rose sharply among those who remained in agriculture (Figure 17b). Because agriculture lies at the bottom of the earnings distribution and accounts for a large share of rural employment (Figure B.6), the combination of shrinking employment and rising wages in this sector substantially reduced the overall inequality—by about 0.06 when combining both the between- and within-components. Low-tech manufacturing is situated in the upper-middle part of the earnings distribution, so its contraction contributed less dramatically to the overall decline in rural inequality (-0.017).

Other sectors in rural regions pushed inequality in the opposite direction. Low-paying industries such as social services and low-skilled services expanded rapidly but experienced relatively slow wage growth. As a result, they contributed to a noticeable rise in overall inequality. Using finer industry codes, we find that the expansion in social services is driven mainly by elderly and disability care, reflecting demographic and aging trends in Finland, which are more pronounced in rural areas.

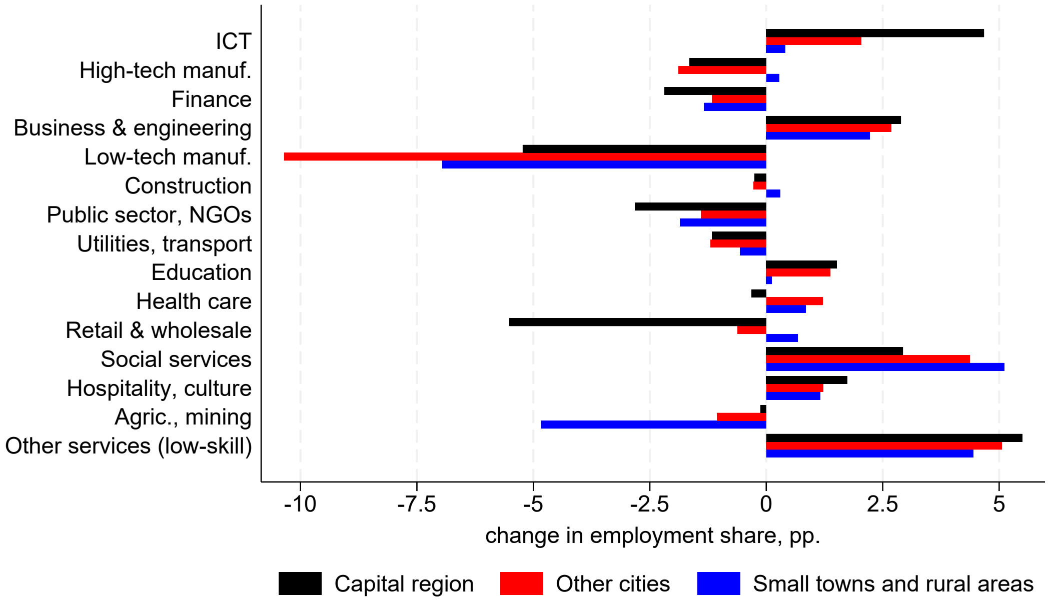
5 Conclusion

This paper has presented new evidence on the evolution of earnings inequality and income dynamics in Finland over three decades. The most striking development was the deep recession of the early 1990s, during which inequality rose sharply as earnings at the bottom collapsed and many indicators failed to return to their pre-crisis levels. Subsequent changes in the 2000s were far less dramatic but cemented the new distributional structure established during the crisis years. We also documented pronounced gender differences, with women's inequality dynamics strongly influenced by childbearing ages, while older women's outcomes resembled those of men much more closely.

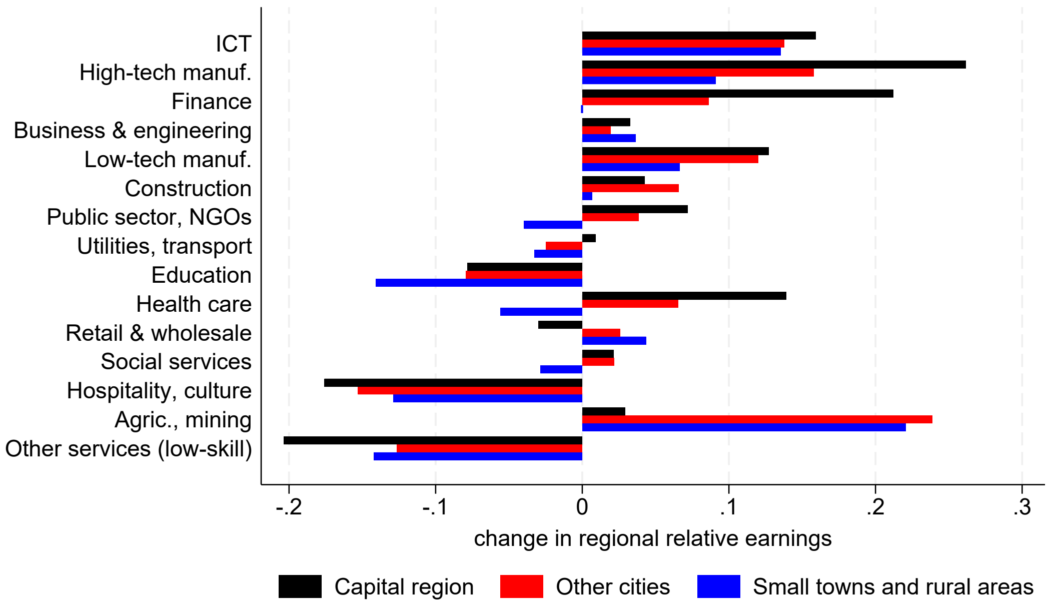
Regional patterns reveal further heterogeneity. Although mean incomes converged across regions after 1995, inequality evolved in opposite directions: it declined in rural areas but continued to rise in Helsinki and other cities. This paper has focused on the role that industrial restructuring plays for these divergent trends. In Helsinki, inequality widened both across and within industries. High-paying sectors such as ICT and business services expanded rapidly with rising wages, while low-wage sectors such as low-skill services and hospitality also grew but saw little wage growth. In contrast, rural inequality declined as employment contracted in agriculture and low-tech manufacturing—sectors located near the bottom and middle of the earnings distribution—though the expansion of social services partially offset this equalizing effect.

Overall, the findings highlight how large structural shocks can leave long-lasting imprints on the income distribution, not only through immediate employment and wage adjustments but also through persistent differences in regional industrial composition. Finland's experience

Figure 17: Components of between-industry variance



(a) Employment share growth: $\frac{N^k_{2018}}{N_{2018}} - \frac{N^k_{1987}}{N_{1987}}$



(b) Relative earnings growth: $\left(\overline{y}^k_{2018} - \overline{\overline{y}}_{2018}\right) - \left(\overline{y}^k_{1987} - \overline{\overline{y}}_{1987}\right)$

Note: Panel (a) shows the change in each industry's employment share as a fraction of total regional employment. Panel (b) shows the growth of sectoral earnings relative to the growth of mean earnings in the region. Sample is the population 25–55 years old with income above the minimum threshold and nonmissing industry info (industry sample), using 15 industry groupings. Industries are sorted in descending order of national mean industry earnings in 2018. The shorthands used are explained in Table B.1.

illustrates that aggregate convergence can mask deep structural divergence, as regions specialize in sectors that shape distinct and enduring inequality trajectories.

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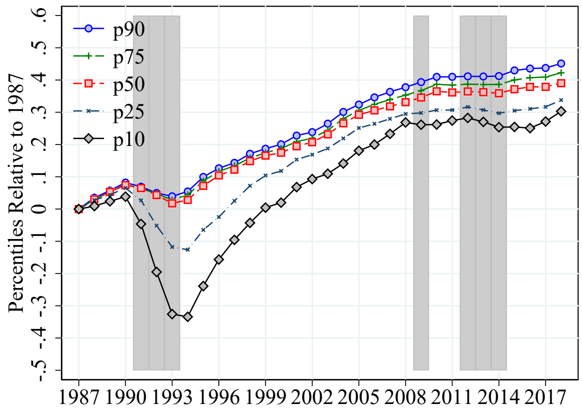
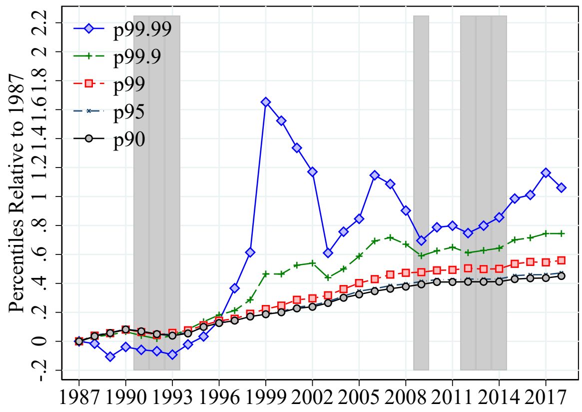
A Appendix Figures: Further GRID analysis

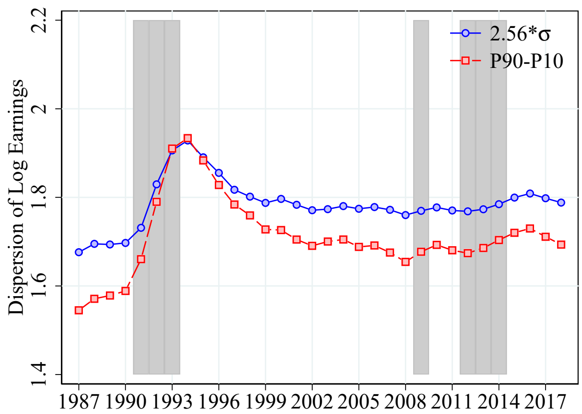
Figure A.1: Distribution of Earnings in the Population



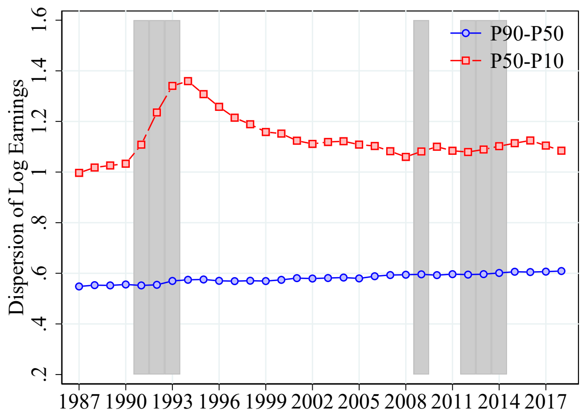
(a) Percentiles



(b) Top Percentiles



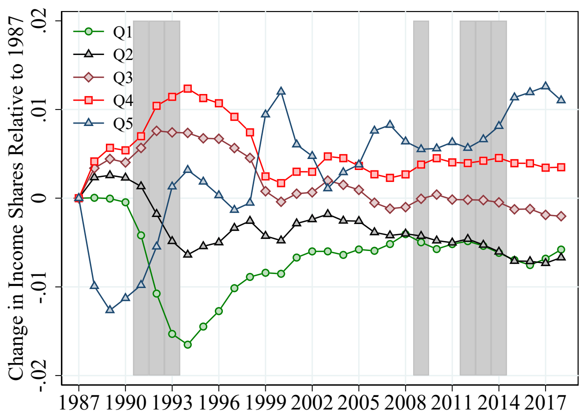
(c) Dispersion



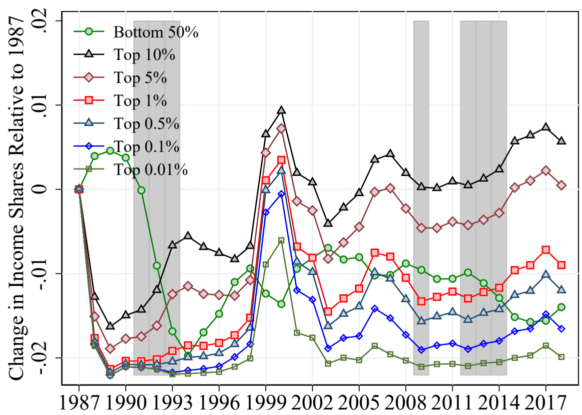
(d) Right- and Left-Tail Dispersion

Note: Using raw log earnings and the CS sample, panels (a) and (b) plot against time various percentiles of the earnings distribution, and panel (c) and (d) the standard deviation and percentile ratios, for the full sample. All percentiles are normalized to 0 in the first available year, 1987 (panels (a) and (b)). 2.56*SD corresponds to P90–P10 differential for a Gaussian distribution. Shaded areas indicate recessions.

Figure A.2: Change in Income Shares Relative to 1987



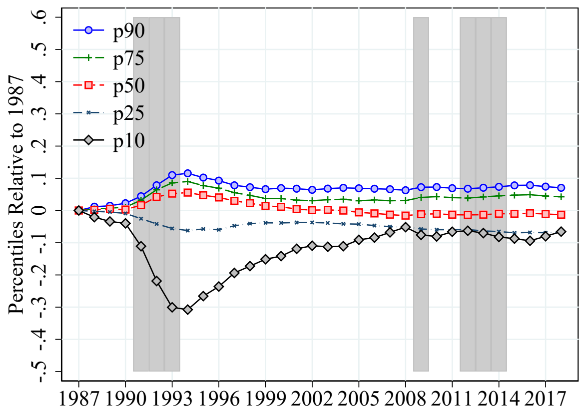
(a) Income Shares of Quintiles



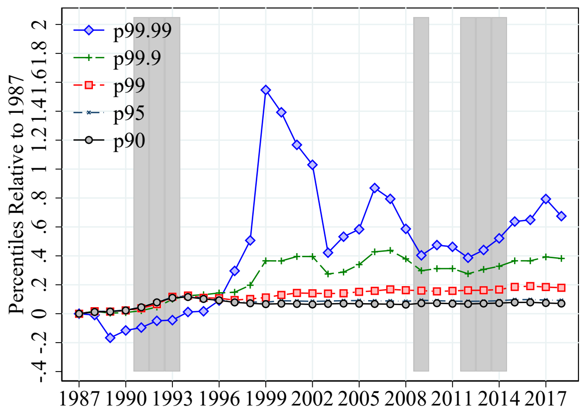
(b) Selected Income Shares

Note: Using raw log earnings and the CS sample, the Figure plots against time the income shares of quintiles and various percentiles, normalized to 0 in the first available year, 1987. Shaded areas indicate recessions.

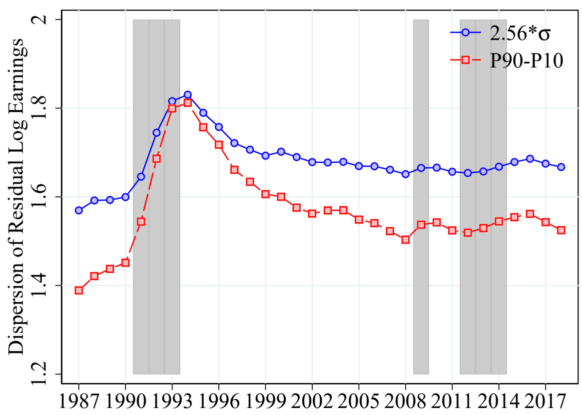
Figure A.3: Distribution of Residual Earnings in the Population After Controlling for Age



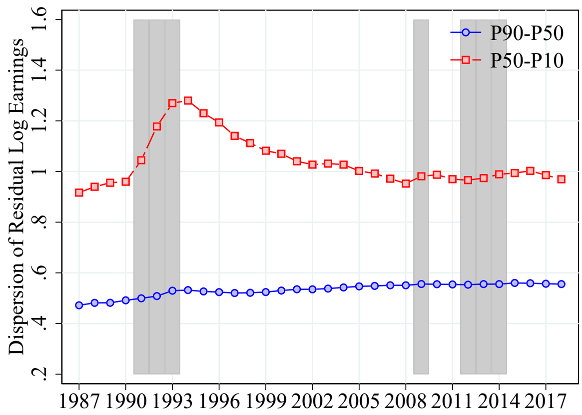
(a) Percentiles



(b) Top Percentiles



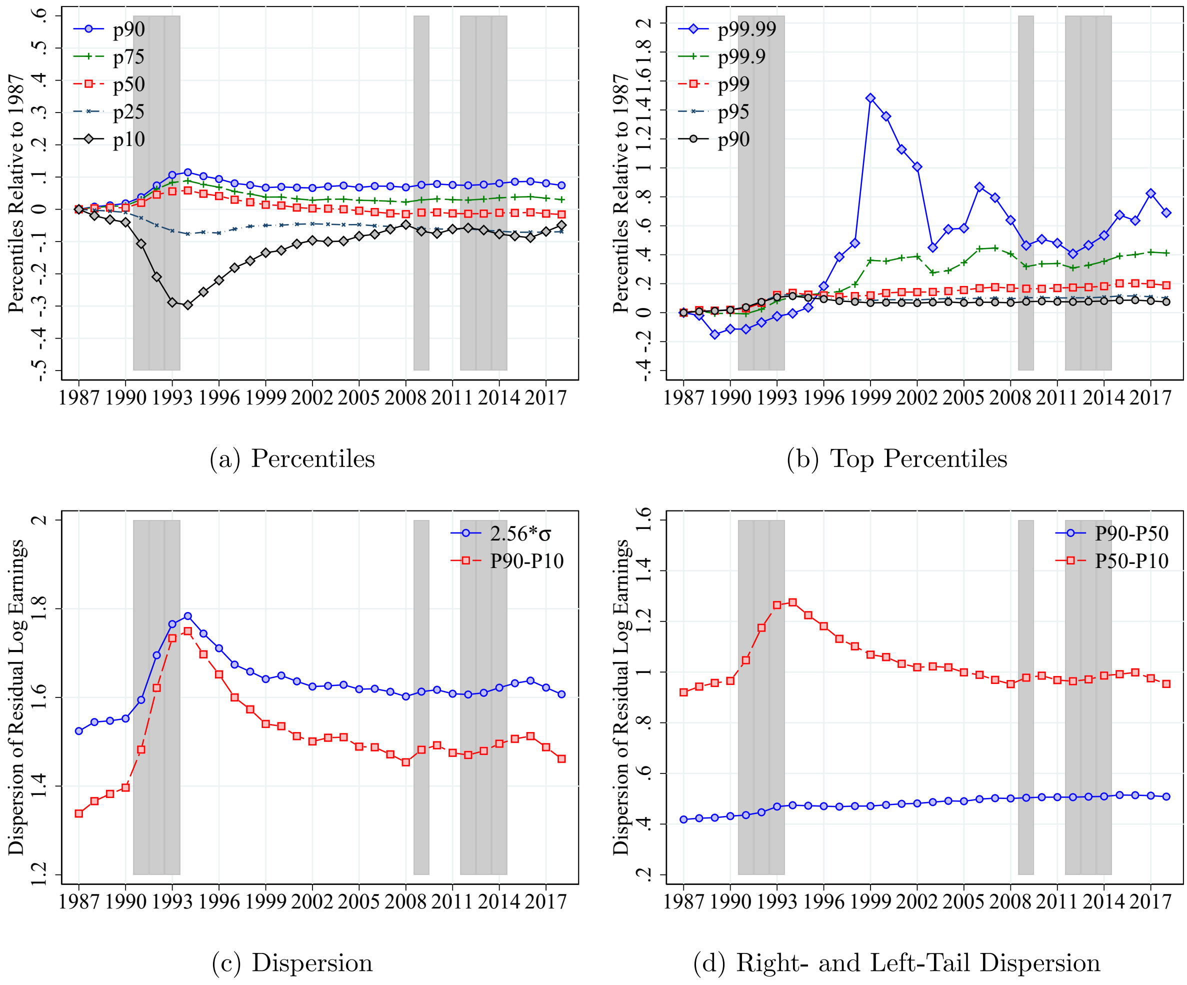
(c) Dispersion



(d) Right- and Left-Tail Dispersion

Note: Using residual log earnings and the CS sample, panels (a) and (b) plot against time various percentiles of the earnings distribution, and panel (c) and (d) the standard deviation and percentile ratios, for the full sample. All percentiles are normalized to 0 in the first available year, 1987 (panels (a) and (b)). 2.56*SD corresponds to P90–P10 differential for a Gaussian distribution. Residual log earnings ε_{it} are obtained by regressing real log earnings on a full set of age dummies separately for each year and gender and then saving the residuals. Shaded areas indicate recessions.

Figure A.4: Distribution of Residual Earnings in the Population After Controlling for Age and Education



(a) Percentiles

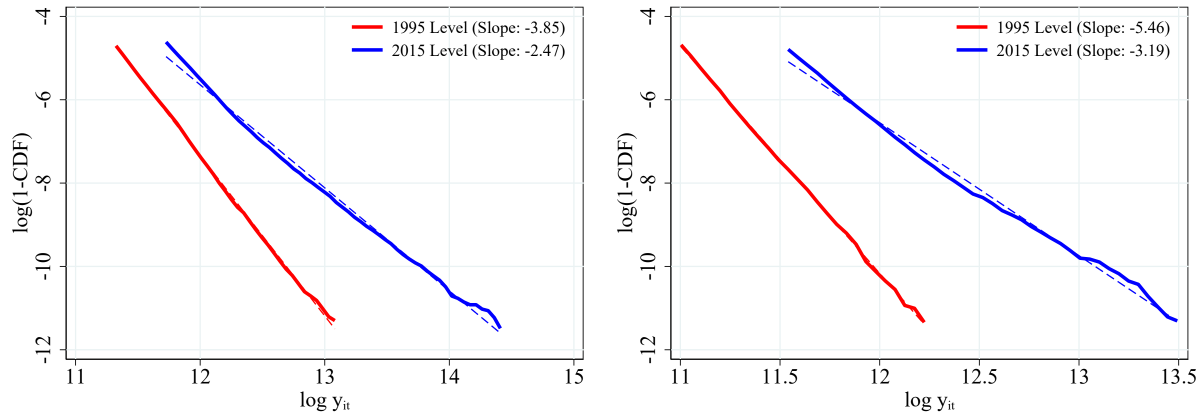
(b) Top Percentiles

(c) Dispersion

(d) Right- and Left-Tail Dispersion

Note: Using residual log earnings and the CS sample, panels (a) and (b) plot against time various percentiles of the earnings distribution, and panel (c) and (d) the standard deviation and percentile ratios, for the full sample. All percentiles are normalized to 0 in the first available year, 1987 (panels (a) and (b)). 2.56*SD corresponds to P90–P10 differential for a Gaussian distribution. Residual log earnings ε_{it} are obtained by regressing real log earnings on a full set of age dummies and a dummy for high education (above high school) separately for each year and gender and then saving the residuals. Shaded areas indicate recessions.

Figure A.5: Top Income Inequality: Pareto Tail at Top 1%

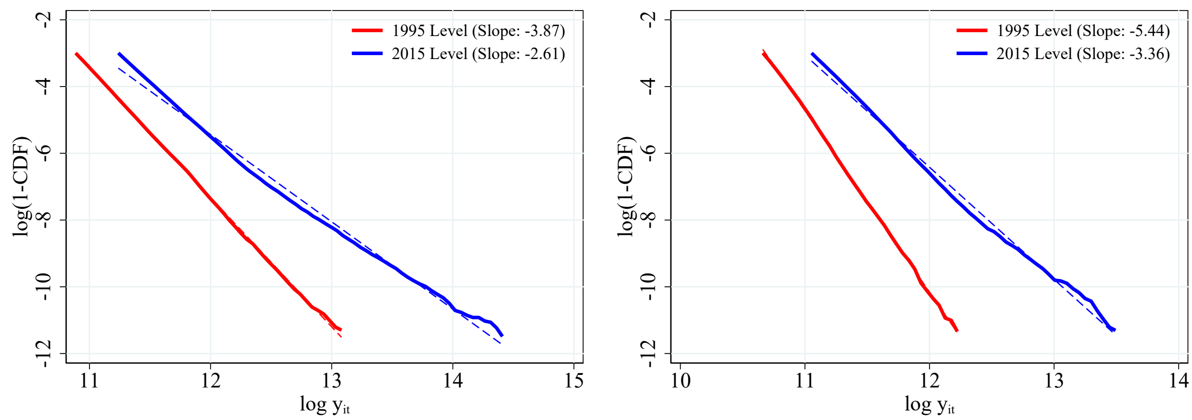


(a) Men

(b) Women

Note: Using raw log earnings and the CS sample, the Figure plots against log income y_{it} in the top 1% of the distribution for men and women separately the log of the inverse of the cumulative distribution function, $\log(1 - CDF)$. Linearity indicates a Pareto shape. The slope of $\log(1 - CDF)$ corresponds to the Pareto α and is displayed in the top right corner.

Figure A.6: Top Income Inequality: Pareto Tail at Top 5%

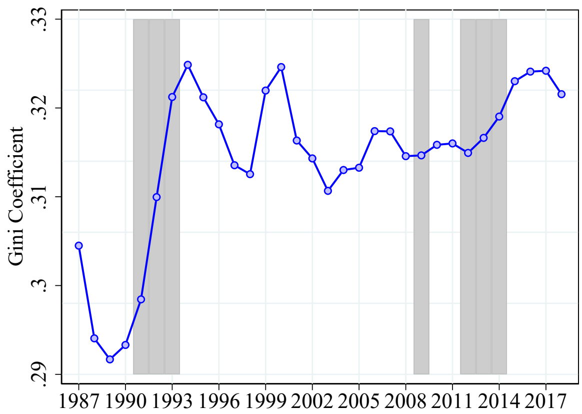


(a) Men

(b) Women

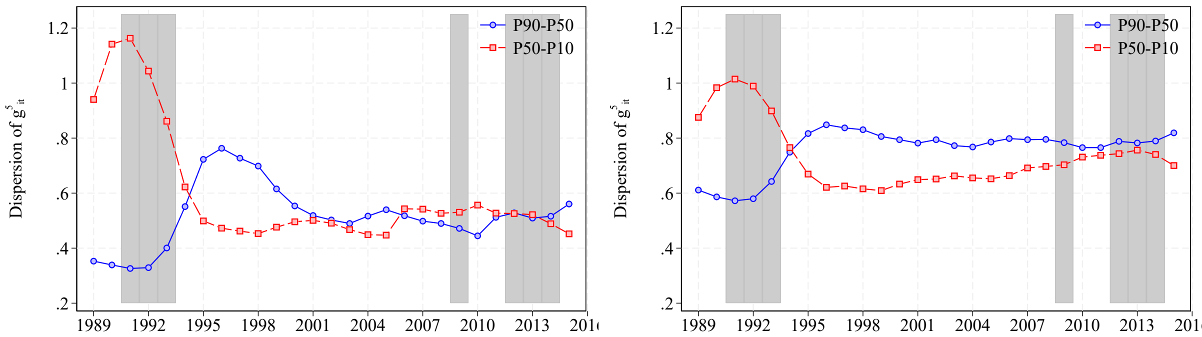
Note: Using raw log earnings and the CS sample, the Figure plots against log income y_{it} in the top 5% of the distribution for men and women separately the log of the inverse of the cumulative distribution function, $\log(1 - CDF)$. Linearity indicates a Pareto shape. The slope of $\log(1 - CDF)$ corresponds to the Pareto α and is displayed in the top right corner.

Figure A.7: Gini Coefficient



Note: Using raw log earnings and the CS sample, the Figure illustrates the Gini coefficient of the total sample. Shaded areas indicate recessions.

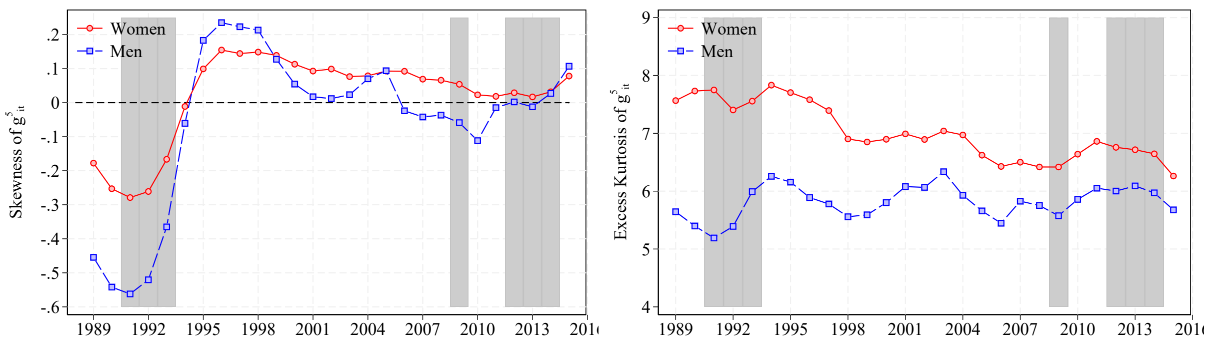
Figure A.8: Dispersion in 5-Year Log Earnings Changes



(a) Men (b) Women

Note: Using residual 5-year earnings changes and the LX sample, the Figure plots against time the P90–P50 and P50–P10 gaps for men and women separately. The time series are recentered into the middle year of the 5-year jump, i.e. the value in year 1989 corresponds to the earnings change from 1987 to 1992. Shaded areas indicate recessions.

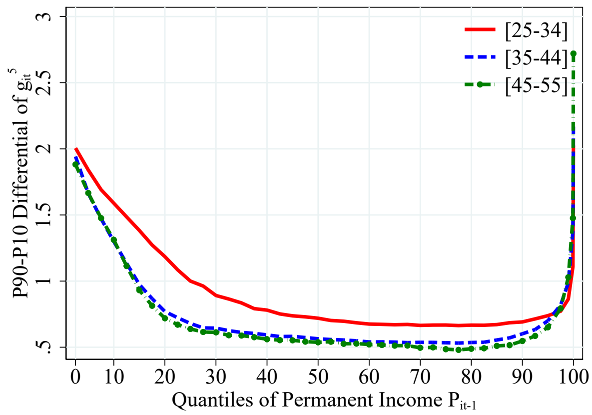
Figure A.9: Skewness and Kurtosis of 5-Year Log Earnings Changes



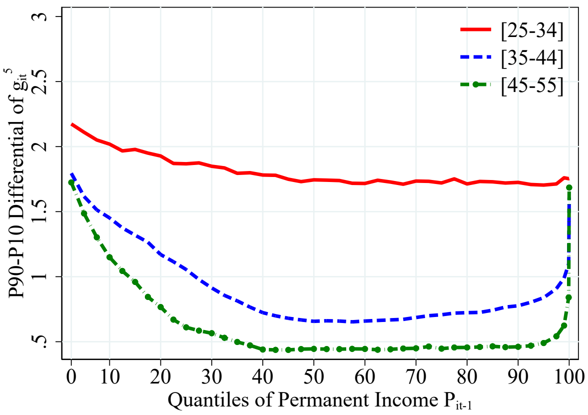
(a) Skewness (b) Excess Kurtosis

Note: Using residual 5-year earnings changes and the LX sample, the Figure plots against time the Kelley skewness, defined as $\frac{(P90-P50)-(P50-P10)}{P90-P10}$, and excess Crow–Siddiqui kurtosis, defined as $\frac{P97.5-P2.5}{P75-P25} - 2.91$, for men and women separately. A normal distribution has Kelley Skewness equal to zero and Crow-Siddiqui kurtosis equal to 2.91. The time series are recentered into the middle year of the 5-year jump, i.e. the value in year 1989 corresponds to the earnings change from 1987 to 1992. Shaded areas indicate recessions.

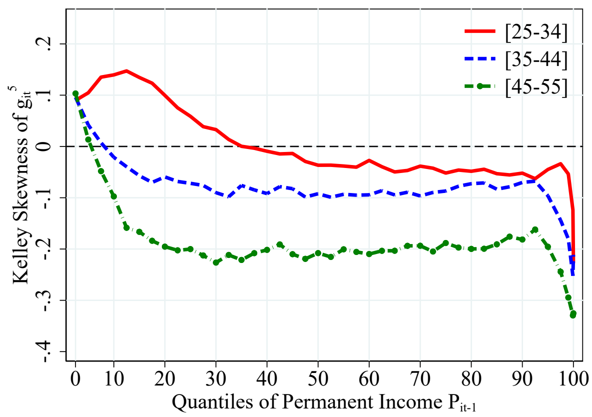
Figure A.10: Dispersion, Skewness and Kurtosis of 5-Year Log Earnings Changes



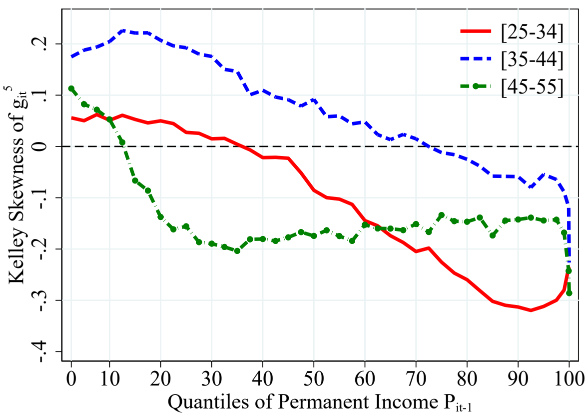
(a) Men



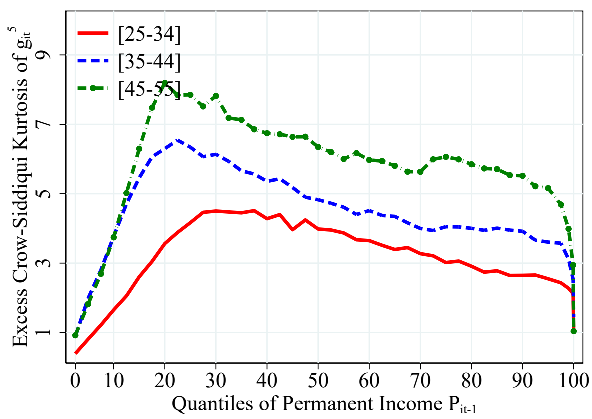
(b) Women



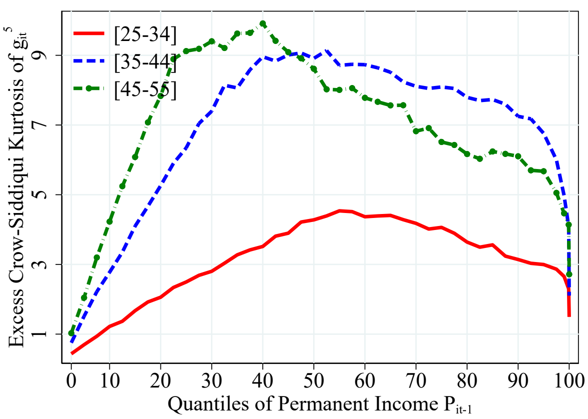
(c) Men



(d) Women



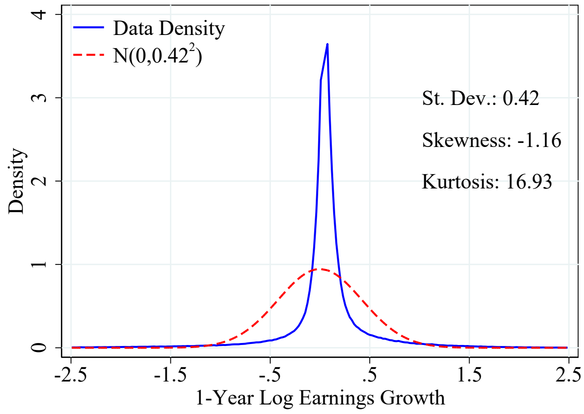
(e) Men



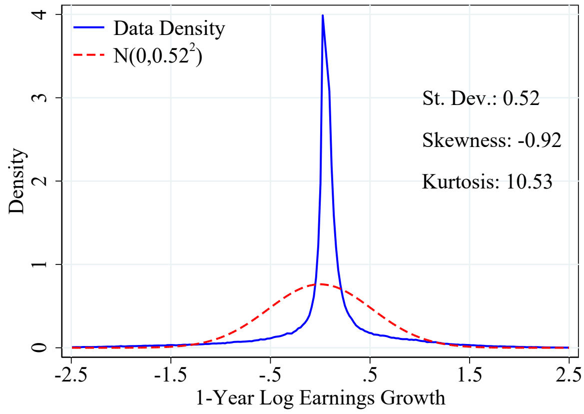
(f) Women

Note: Using residual 5-year earnings changes and the H sample, the Figure plots against permanent income quantile groups the following variables for the three age groups, for men and women separately: P90–P10, Kelley skewness, and Crow-Siddiqui kurtosis. Kelley skewness is defined as $\frac{(P90-P50)-(P50-P10)}{P90-P10}$. Excess Crow–Siddiqui kurtosis is defined as $\frac{P97.5-P2.5}{P75-P25} - 2.91$. A normal distribution has Kelley Skewness equal to zero and Crow-Siddiqui kurtosis equal to 2.91. The Figure presents average outcomes across the years during 1999–2013.

Figure A.11: Empirical Densities of 1-Year Earnings Growth



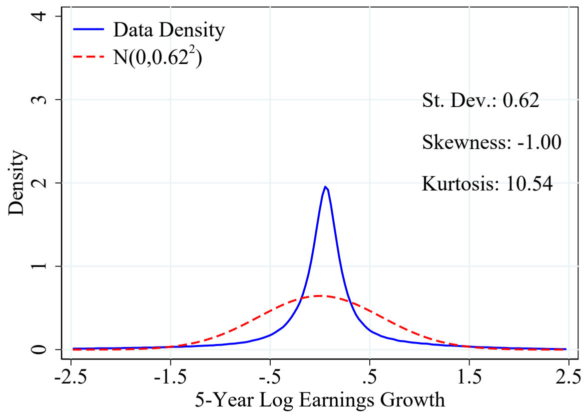
(a) Men



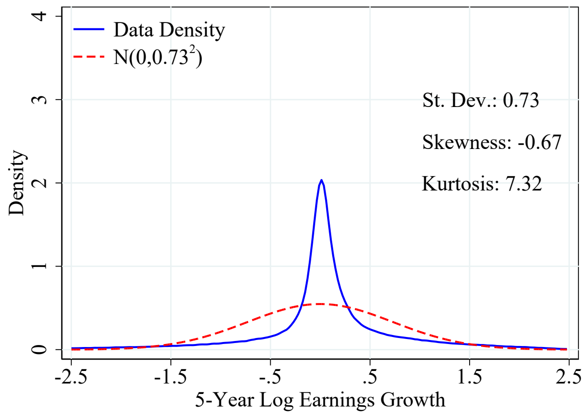
(b) Women

Note: Using residual 1-year earnings changes and the LX sample, the Figure plots the empirical density of log earnings changes in 2005 for men and women separately, and a normal distribution with a standard deviation equal to the empirical standard deviation. The properties of the empirical density (standard deviation, skewness, kurtosis) are displayed in the graphs.

Figure A.12: Empirical Densities of 5-Year Earnings Growth



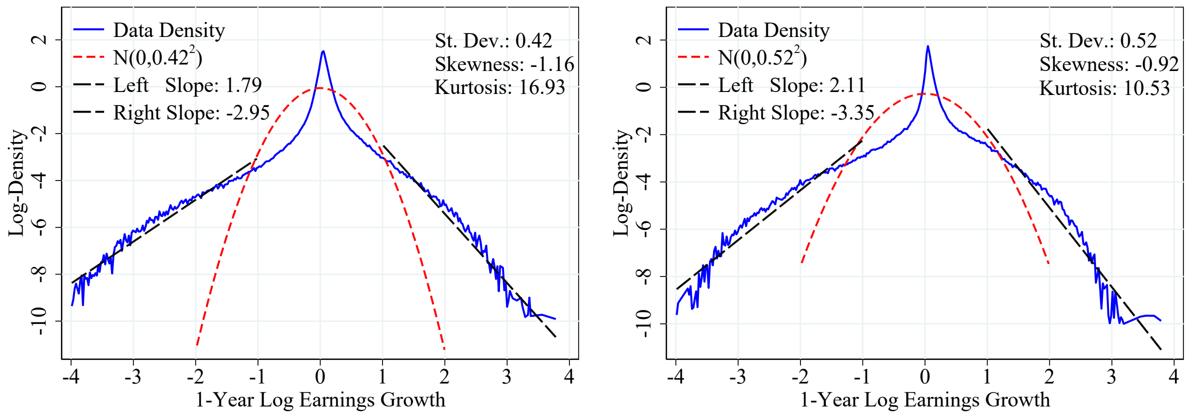
(a) Men



(b) Women

Note: Using residual 5-year earnings changes and the LX sample, the Figure plots the empirical density of log earnings changes in 2005 for men and women separately, and a normal distribution with a standard deviation equal to the empirical standard deviation. The properties of the empirical density (standard deviation, skewness, kurtosis) are displayed in the graphs.

Figure A.13: Empirical Log-Densities of 1-Year Earnings Growth

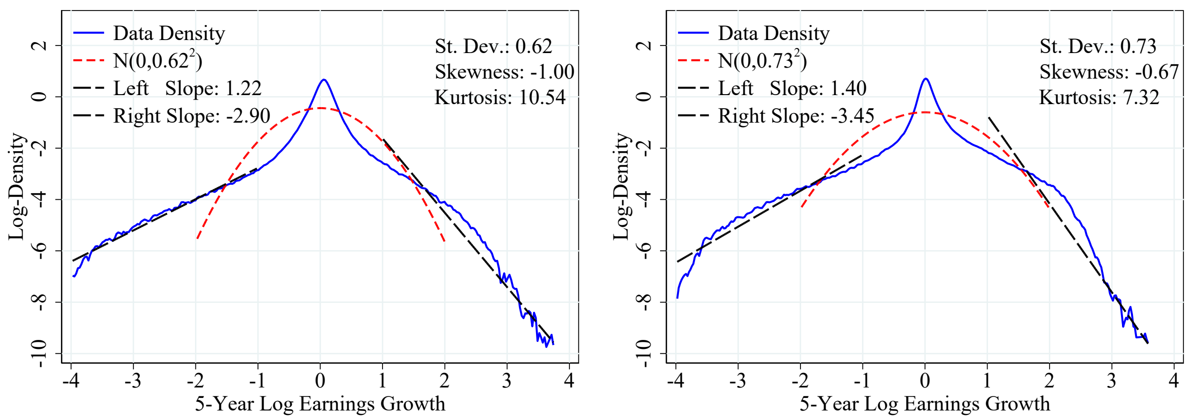


(a) Men

(b) Women

Note: Using residual 1-year earnings changes and the LX sample, the Figure plots the empirical log density of log earnings changes in 2005 for men and women separately, and a normal distribution log density with a standard deviation equal to the empirical standard deviation. The properties of the empirical density (standard deviation, skewness, kurtosis) are displayed in the graphs, along with estimates for the left and right slopes of the log density.

Figure A.14: Empirical Log-Densities of 5-Year Earnings Growth

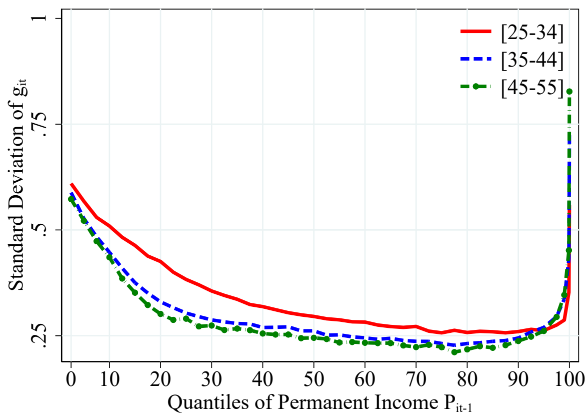


(a) Men

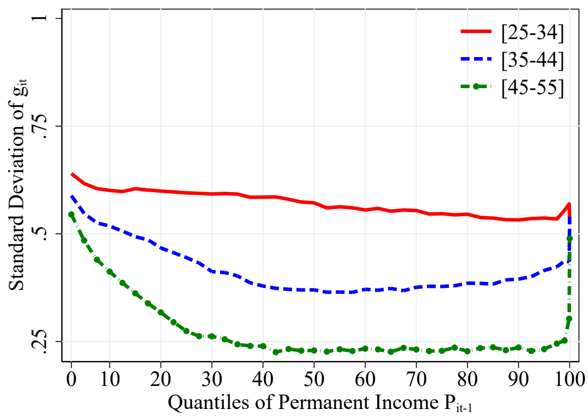
(b) Women

Note: Using residual 5-year earnings changes and the LX sample, the Figure plots the empirical log density of log earnings changes in 2005 for men and women separately, and a normal distribution log density with a standard deviation equal to the empirical standard deviation. The properties of the empirical density (standard deviation, skewness, kurtosis) are displayed in the graphs, along with estimates for the left and right slopes of the log density.

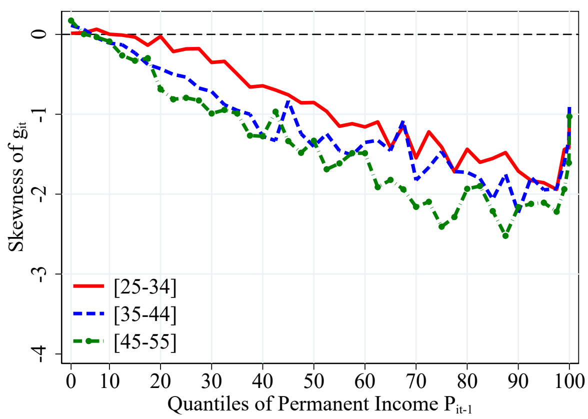
Figure A.15: Standardized Moments of 1-Year Earnings Changes



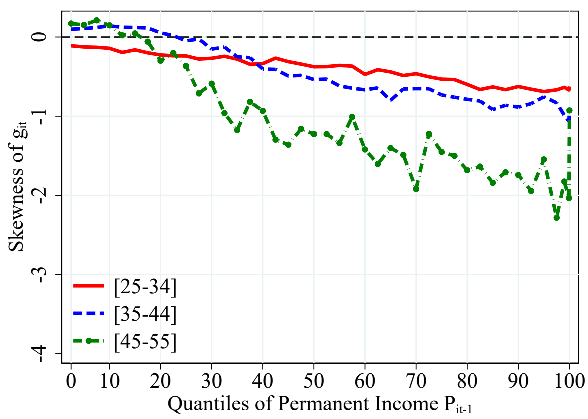
(a) Men



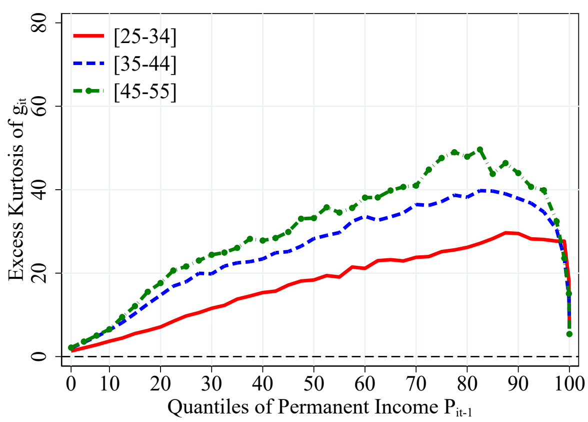
(b) Women



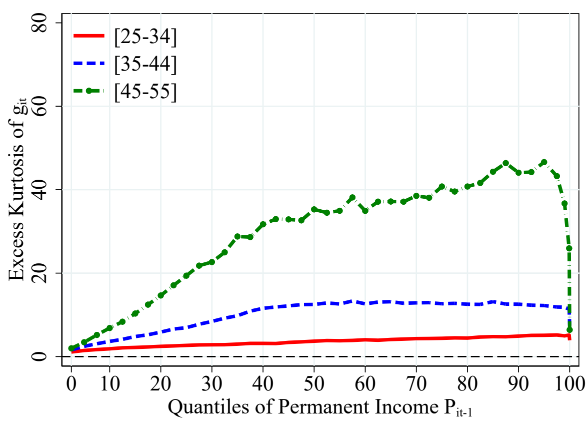
(c) Men



(d) Women



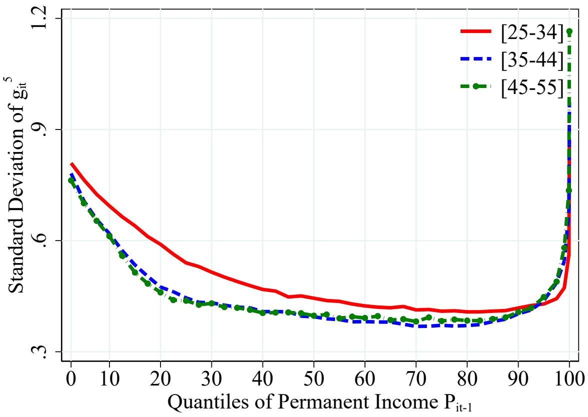
(e) Men



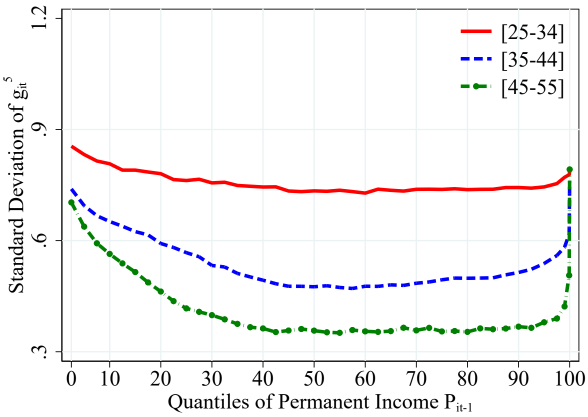
(f) Women

Note: Using residual 1-year earnings changes and the H sample, the Figure plots against permanent income quantile groups the following variables for the three age groups, for men and women separately: standard deviation, skewness and excess kurtosis. A normal distribution has skewness equal to zero and kurtosis equal to 3. The Figure presents average outcomes across the years during 1999–2013.

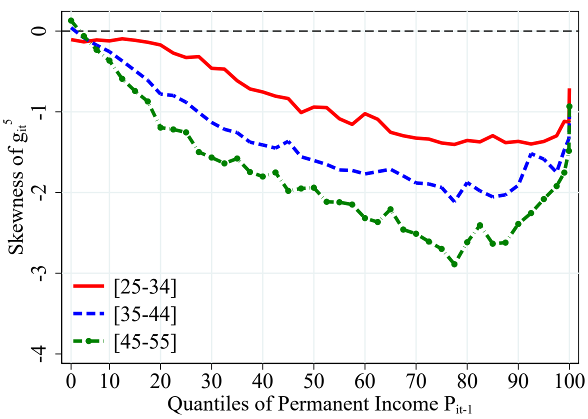
Figure A.16: Standardized Moments of 5-Year Earnings Changes



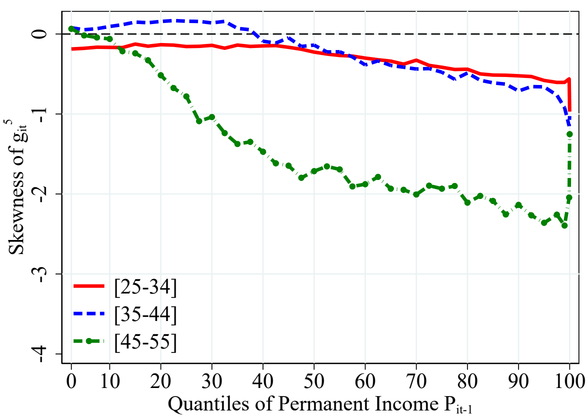
(a) Men



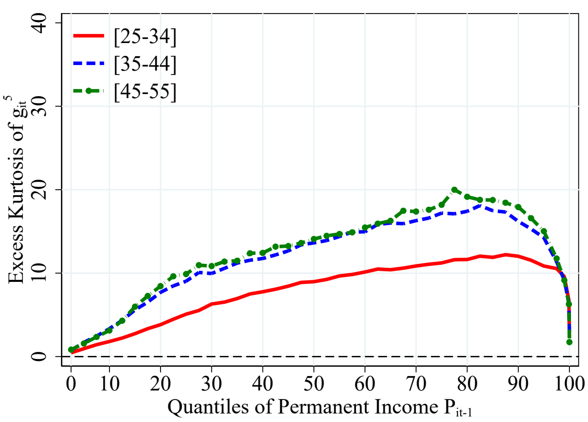
(b) Women



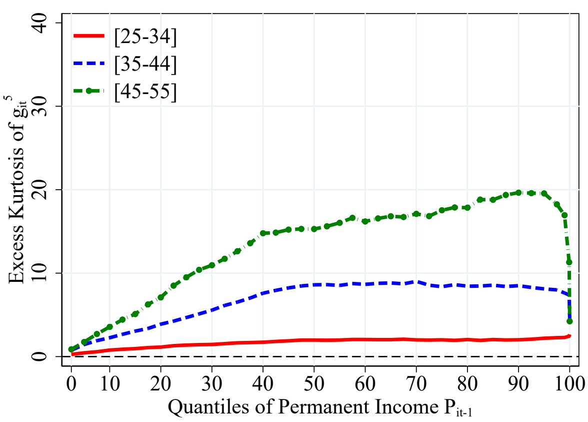
(c) Men



(d) Women



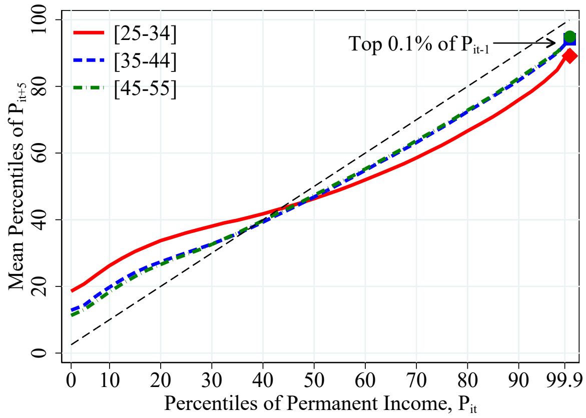
(e) Men



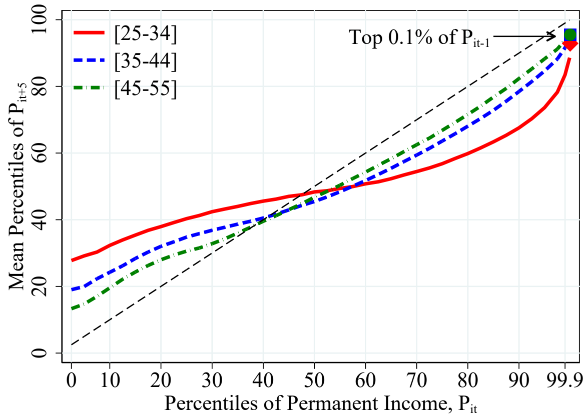
(f) Women

Note: Using residual 5-year earnings changes and the H sample, the Figure plots against permanent income quantile groups the following variables for the three age groups, for men and women separately: standard deviation, skewness and excess kurtosis. A normal distribution has skewness equal to zero and kurtosis equal to 3. The Figure presents average outcomes across the years during 1999–2013.

Figure A.17: Evolution of 5-Year Mobility Over the Life Cycle



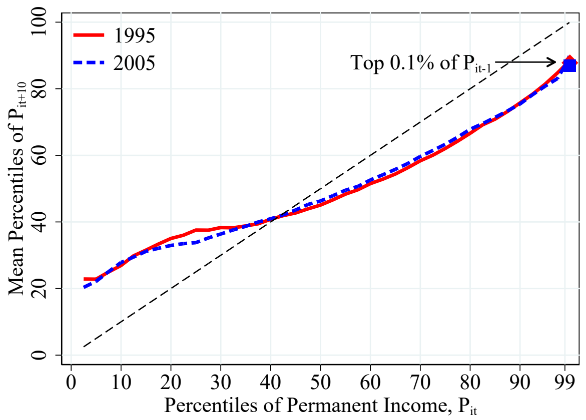
(a) Men



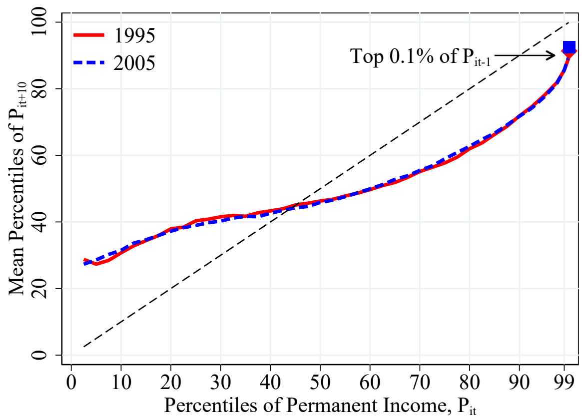
(b) Women

Note: Using permanent income and the H sample, the Figure shows average rank-rank mobility over 5 years by computing average percentiles of permanent income 5 years later for workers in each permanent income percentile in the base year, for men and women and age groups separately, and taking the average across all years in the data.

Figure A.18: Evolution of 10-Year Mobility Over Time



(a) Men

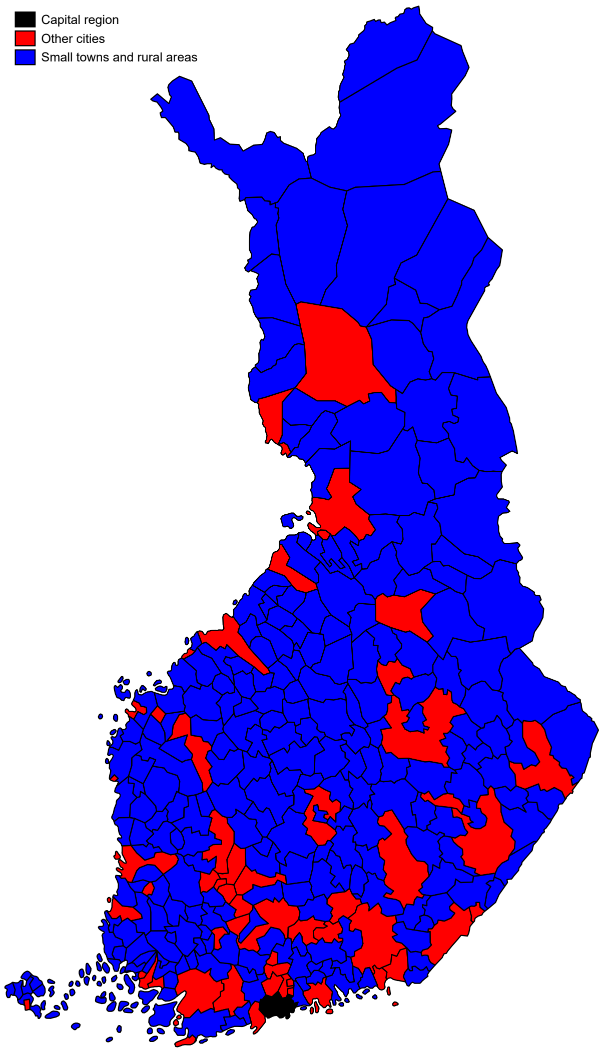


(b) Women

Note: Using permanent income and the H sample, the Figure shows rank-rank mobility over 10 years in base years 1995 and 2005 by computing average percentiles of permanent income 10 years later for workers in each permanent income percentile in the base year, for men and women separately.

B Appendix Figures: Regional and industry analysis

Figure B.1: Distribution of regions on map



Note: Figure shows the map of municipalities in 2020 and the colors illustrate which region type the municipalities belong to. During the time period studied, there have been numerous municipality mergers, and municipalities can have changed their municipality type classification. Throughout the analysis, we use the municipality and region classifications in 2020, so the definitions are consistent over time.

Table B.1: 15 industry groups

Industry shorthand	Industry description
Agric., mining	Agriculture, forestry, fishery, mining
Low-tech manuf.	Low-tech manufacturing
High-tech manuf.	High-tech manufacturing
Utilities, transport	Energy supply, water supply, waste management, transportation, warehousing, mail, courier
Construction	Construction
Retail & wholesale	Retail trade, wholesale trade, vehicle trade
Hospitality, culture	Hotels, restaurants, culture, recreation
ICT	IT and telecommunication services
Finance	Finance, insurance, real estate
Business & engineering	Business management, engineering activities, R&D
Other services	Other services (e.g. employment services, security services, hair salons, cleaning services, services to buildings)
Public sector, NGOs	Public administration, public order, national defense, non-profit organizations, international organizations
Education	Education
Health care	Health care
Social services	Social services (e.g. elderly and disabled care, child day care, care for substance abuse)

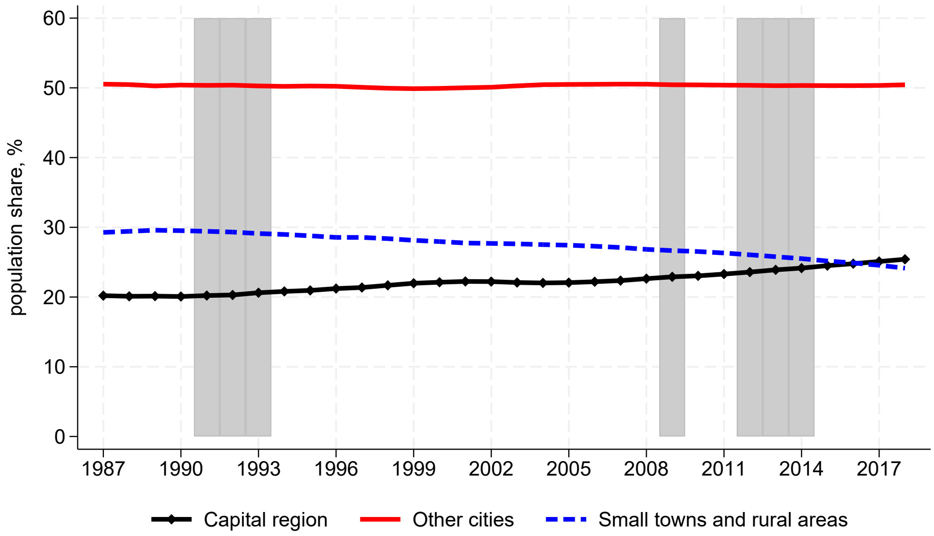
Note: Manufacturing sectors are divided into high and low-tech sectors based on Eurostat categorisation (see `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries`. High-tech includes both high and medium-high technology sectors, low-tech includes low and medium-low technology sectors.

Table B.2: Variance decomposition

	1987–1989	2016–2018	Growth
Country total			
Total variance	0.312	0.405	0.094
Within-industry	0.287	0.364	0.077
Between-industry	0.025	0.041	0.016
Within-industry, % of total	92.1	89.9	82.6
Between-industry, % of total	7.9	10.1	17.4
Capital region			
Total variance	0.307	0.496	0.189
Within-industry	0.293	0.438	0.145
Between-industry	0.014	0.058	0.044
Within-industry, % of total	95.5	88.4	76.8
Between-industry, % of total	4.5	11.6	23.2
Other cities			
Total variance	0.274	0.386	0.112
Within-industry	0.257	0.347	0.090
Between-industry	0.018	0.039	0.022
Within-industry, % of total	93.6	89.8	80.5
Between-industry, % of total	6.4	10.2	19.5
Small towns and rural areas			
Total variance	0.347	0.341	–0.006
Within-industry	0.307	0.311	0.004
Between-industry	0.040	0.030	–0.009
Within-industry, % of total	88.5	91.1	–60.8
Between-industry, % of total	11.5	8.9	160.8

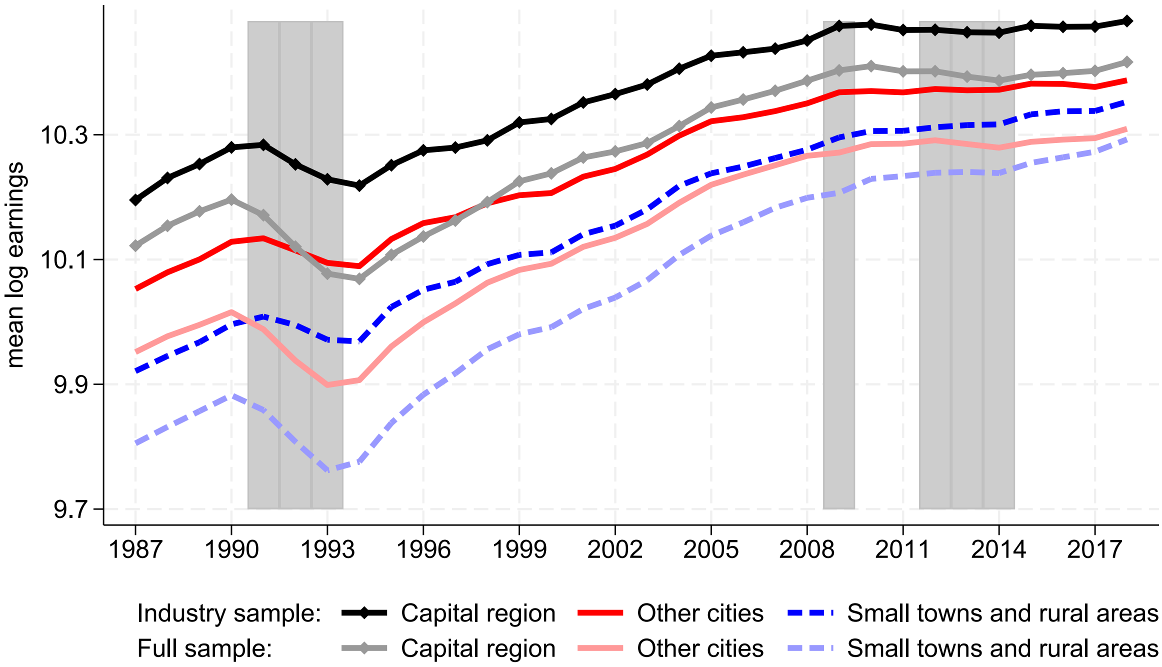
Notes: The Table shows the between- and within industry variance (see Eq. (1)) over time and nationally and for each region using the population 25–55 years old with income above the minimum threshold and nonmissing industry info (industry sample) using 15 industry groupings.

Figure B.2: Population shares of regions

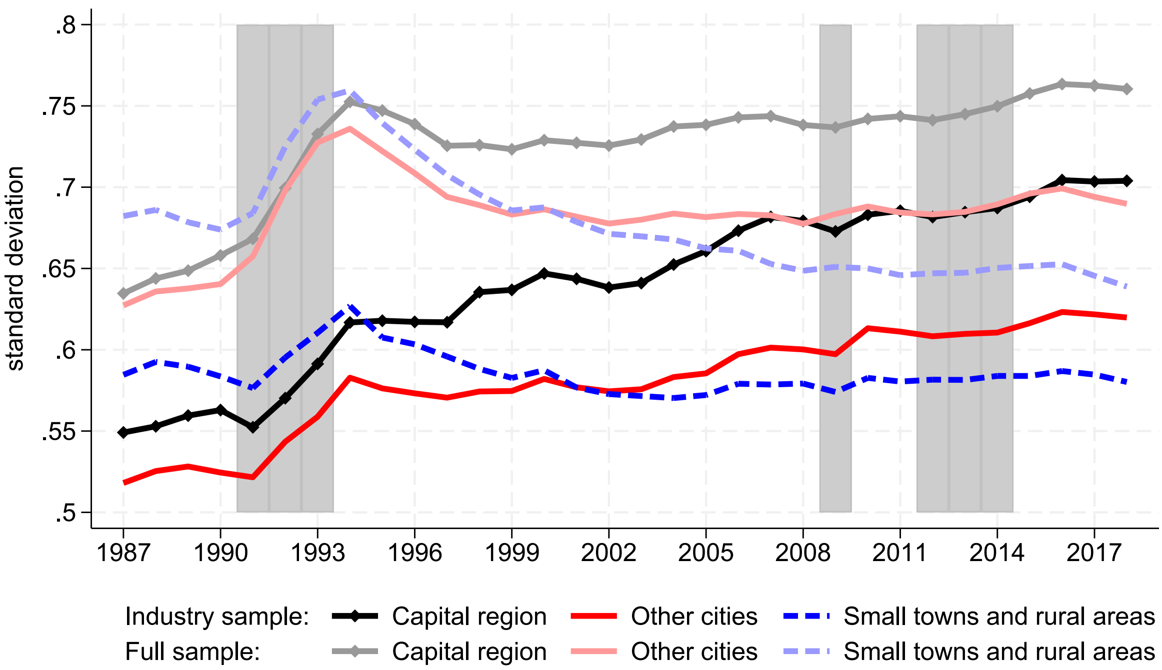


Note: The Figure shows the share of the population in each region across time in the sample of 25–55-year-old individuals with income above the minimum annual earnings threshold (CS sample). Shaded areas indicate recessions.

Figure B.3: Earnings distribution in industry sample and CS sample



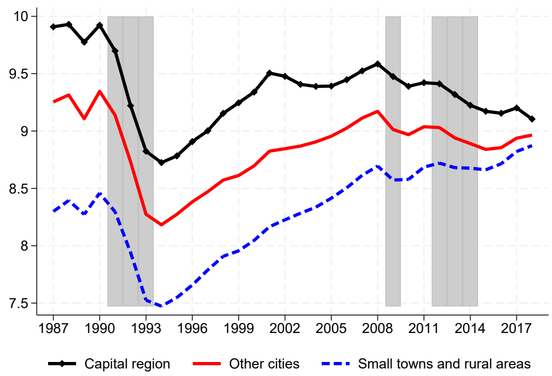
(a) Mean log earnings



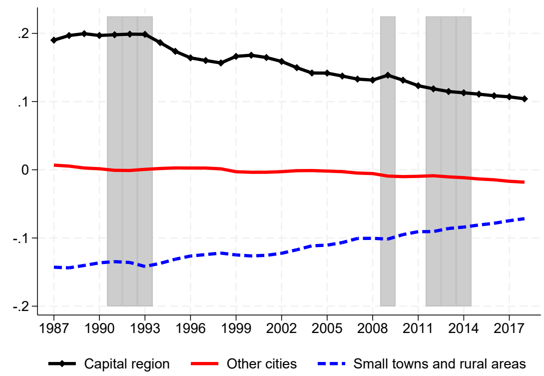
(b) Standard deviation in log earnings

Note: *Industry sample* consists of individuals whose annual earnings are above the minimum earnings threshold, who are recorded as employed at the end of the calendar year, and have an industry code. *Full sample* is the sample of individuals whose annual earnings are above the minimum earnings threshold (CS sample). Both samples are restricted to 25–55-year-olds. Shaded areas indicate recessions.

Figure B.4: Convergence in mean log earnings across regions



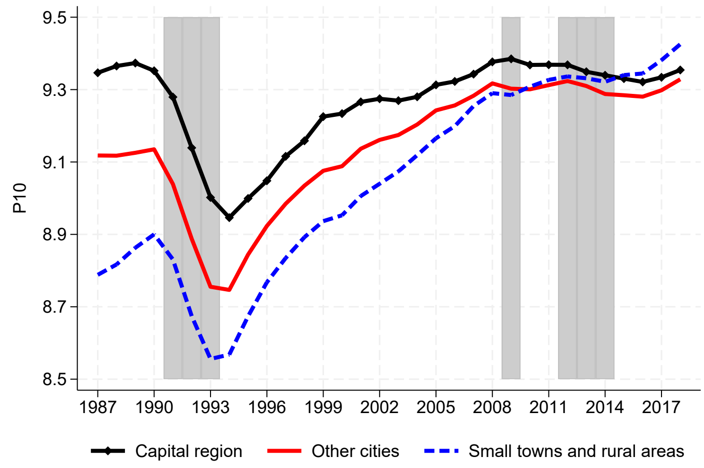
(a) Mean asinh(earnings) (including zeros)



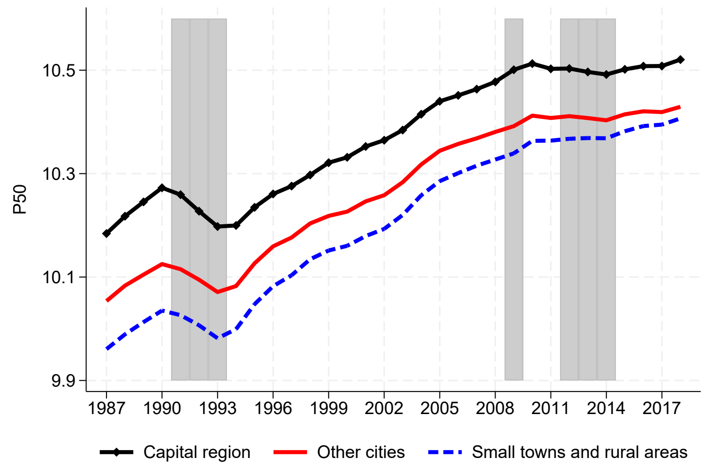
(b) Mean residualized earnings

Note: In panel (a) asinh(earnings) is the inverse hyperbolic sine of real annual earnings, calculated with total population aged 25–55 (including those with earnings below the minimum earnings threshold and with zero earnings) as $asinh(y) = ln(y + \sqrt{y^2 + 1})$. In panel (b) residualised log earnings ε_{it} are obtained by regressing real log earnings on a full set of age dummies separately for each year and gender and then saving the residuals, similarly as in Section 3.2. Shaded areas indicate recessions.

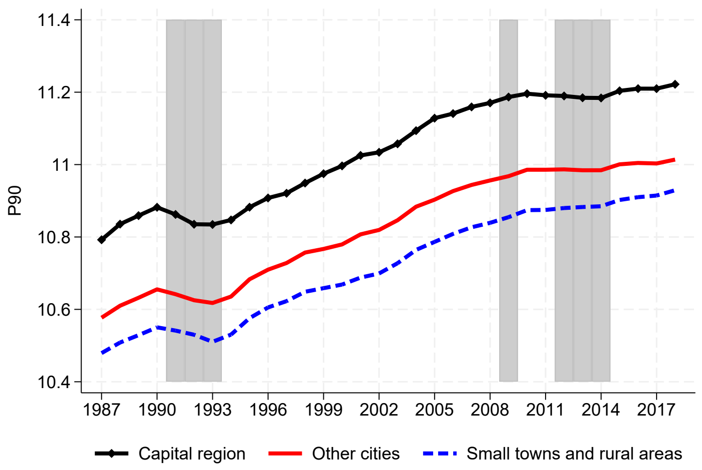
Figure B.5: Time trends in P10, P50 and P90 across regions



(a) P10



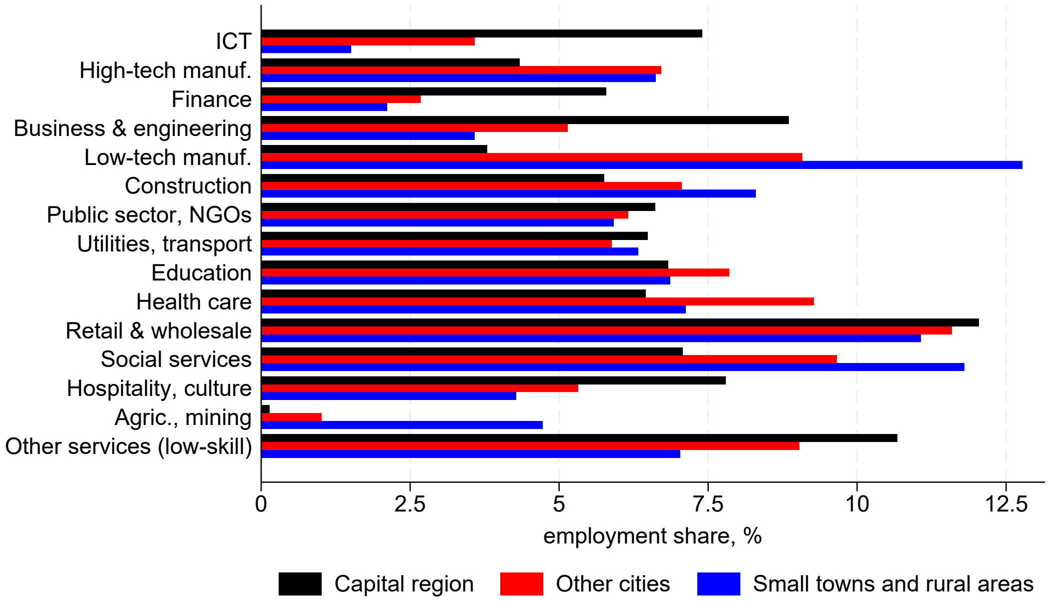
(b) P50



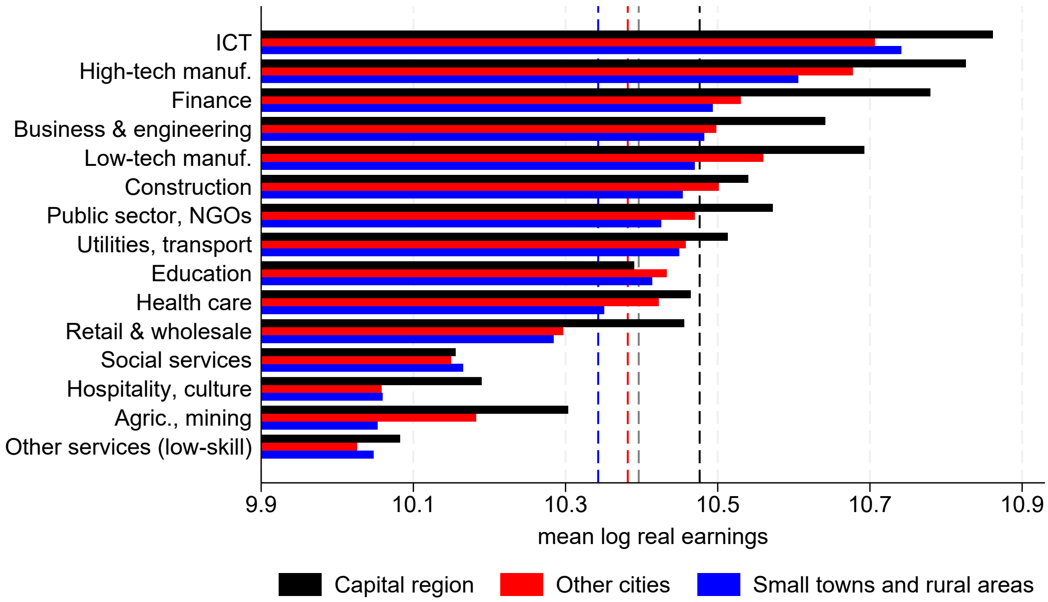
(c) P90

Note: The Figure shows various percentiles of the raw log real annual earnings distribution across time by region. Sample includes 25–55-year old individuals with income above the minimum annual earnings threshold (CS sample). Shaded areas indicate recessions. Shaded areas indicate recessions.

Figure B.6: Industry composition and mean earnings by region



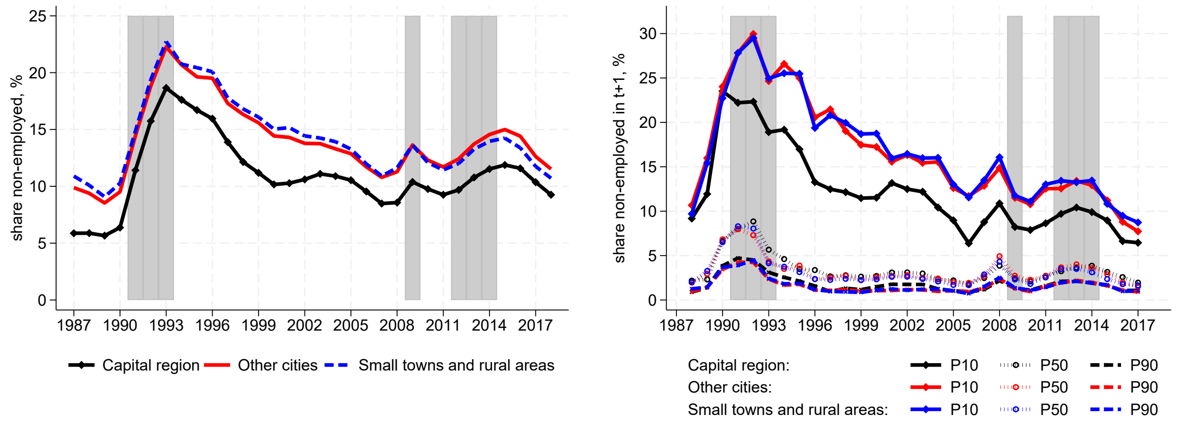
(a) Employment share in 2018



(b) Mean earnings in 2018

Note: The Figure shows the mean employment share and mean log earnings in 2018 (using average of 2016–2018) across industries and regions. Sample is the population 25–55 years old with income above the minimum threshold and nonmissing industry info (industry sample), using 15 industry groupings. Industries are sorted in descending order of national mean industry earnings in 2018. The shorthands used are explained in Table B.1.

Figure B.7: Non-employment and unemployment transition rates across regions: Natives only

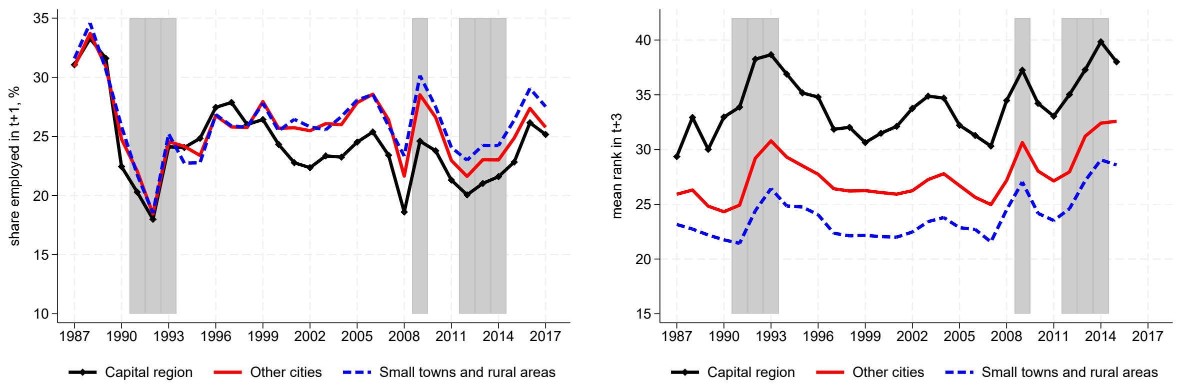


(a) Non-employment rate

(b) Transition rate to unemployment by rank

Note: Graph reproduces Figure 12 with Finnish natives only (individual born in Finland, parents born in Finland). Panel (a) shows the proportion of the population aged 25–55 years who are non-employed (defined as unemployed + out of the labor force). Panel (b) shows the proportion of 25–55-year-olds who have annual earnings above the minimum threshold and are employed at end of the year in year t (horizontal axis) and non-employed at the end of year $t+1$, given their permanent income rank in year t. Individuals are ranked according to their permanent income (see definition in Section 2.1) at the national level. Shaded areas indicate recessions.

Figure B.8: Job finding rate and earnings after finding a job, across regions: Natives only

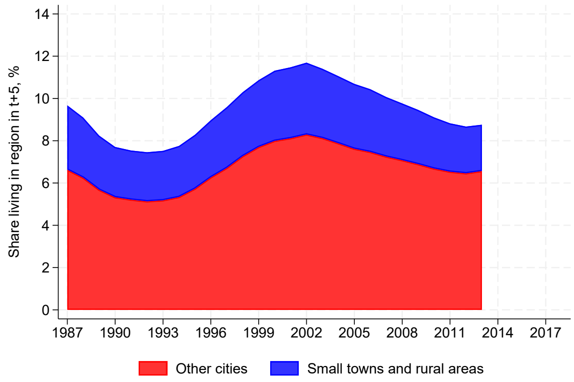


(a) Job finding rate

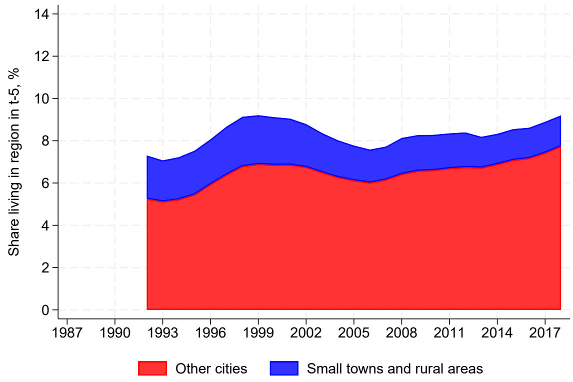
(b) Mean permanent income rank after finding a job

Note: Graph reproduces Figure 13 with Finnish natives only (individual born in Finland, parents born in Finland). Panel (a) shows the proportion of the population aged 25–55 years who are non-employed (defined as unemployed + out of the labor force) at the end of year t (horizontal axis) and employed at the end of $t+1$ with annual income above the minimum threshold. Panel (b) shows the mean permanent income rank in year $t+3$ conditional on having been unemployed at the end of year t (horizontal axis). Individuals are ranked according to their permanent income (see definition in Section 2.1) at the national level. Note that unemployment in t does not affect permanent earnings measure in $t+3$. Unemployed individuals in year $t+3$ are given a rank zero. Shaded areas indicate recessions.

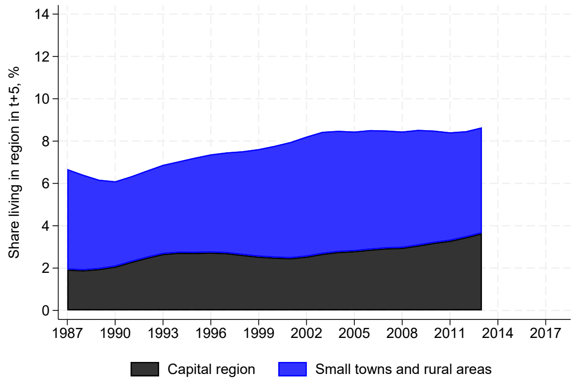
Figure B.9: In- and out-migration by region and origin/destination



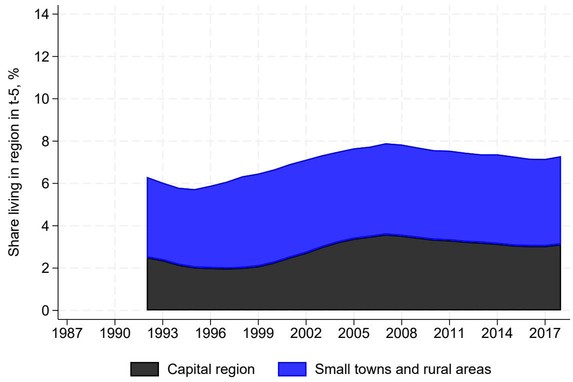
(a) Capital region, out-migration



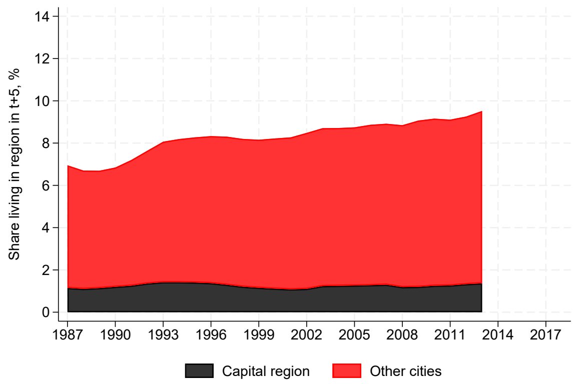
(b) Capital region, in-migration



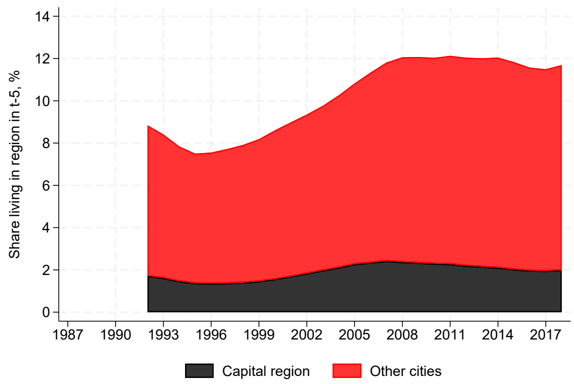
(c) Other cities, out-migration



(d) Other cities, in-migration



(e) Small towns and rural areas, out-migration



(f) Small towns and rural areas, in-migration

Note: Figure shows the share of a region's population in year t (horizontal axis) that moves out of the region to the given destination in the next five years (panels (a), (c), (e)), or has moved into the region within the last five years from the given origin (panels (b), (d), (f)). The shares are calculated as # not living in region in $t+s$ / # population in t, for $s = 5$ or $s = -5$. Sample is full population aged 25–55 years, conditional on being observed in both t and $t+s$.