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Research Paper

Two decades of earnings inequality in Hungary[☆]

István Boza[a,*], Martin Neubrandt[b], Rita Pető[a]

[a] *ELTE Centre for Economic and Regional Studies, Hungary*
[b] *ELTE Centre for Economic and Regional Studies, Corvinus University of Budapest, Hungary*

A B S T R A C T

We use Hungarian administrative microdata harmonized within the Global Repository of Income Dynamics (GRID) framework to study earnings inequality, volatility, and mobility over 2004–2021. Aggregate earnings dispersion changes little over the two decades, with modest increases in top inequality for men and widening lower-tail inequality among young workers. One-year earnings growth shows asymmetric downside risk during recessions, especially for men, and persistently higher volatility, skewness, and kurtosis for prime-age women, consistent with career interruptions around childbearing. In the second part of the paper, we estimate AKM-style wage models with occupation effects for 2004–2010 and 2013–2019. Worker heterogeneity explains about half of wage dispersion in both periods. The role of firm and occupation premia declines, consistent with the strong increase in real minimum wages. Meanwhile, the contribution of worker–firm sorting remains quantitatively important, especially in the bias-corrected specification. Bias-corrected results suggest a strong role of assortativity in the Hungarian labor market.

1. Introduction

This chapter studies earnings inequality, volatility, and mobility in Hungary between 2004 and 2021 using administrative microdata harmonized within the Global Repository of Income Dynamics (GRID) framework. The studied period was characterized by strong real wage growth and substantial increases in statutory wage floors, alongside only modest changes in aggregate earnings dispersion. Following the first wave of GRID studies, we apply common definitions, sampling rules, and summary statistics to ensure cross-country comparability. We then extend the harmonized analysis with a country-specific linked employer–employee decomposition, separating worker, firm, and occupation components of hourly wage dispersion.

We begin our examination by documenting the evolution of inequality using percentile summaries and P90–P10/P90–P50/P50–P10 gaps. Hungary shows modest changes in overall dispersion over two decades, with movements concentrated around the lower half and around major policy and business-cycle episodes. Volatility and distributional shape (Kelley skewness and Crow–Siddiqui kurtosis) of one-year earnings growth reveal asymmetric downside risk during recessions, especially for men, and persistently higher volatility for prime-age women. Mobility over ten-year horizons remains limited and concentrated at the bottom, with younger women showing somewhat stronger upward movement from low initial positions. These patterns suggest that Hungary is one of the GRID countries where overall inequality has remained fairly stable. At the same time, risk and mobility differ across income groups and over the life cycle.

In the second part of the paper, we apply an AKM-style wage decomposition (augmented with occupation effects) over two seven-year windows (2004–2010 and 2013–2019). Overall wage dispersion declines modestly over the period, a pattern consistent with substantial increases in the minimum wage and compression at the lower end of the wage distribution. In the earnings analysis, this decline in wage dispersion is offset by increasing dispersion in working hours, especially among low earners. One key question is how this compression appears in the wage structure: through greater similarity in workers' persistent earnings, convergence in firms' pay policies, narrower occupational premia, or changes in how workers sort into firms and occupations.

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* Corresponding author.
E-mail address: boza.istvan@krtk.hu (I. Boza).

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Three findings stand out. First, worker heterogeneity explains roughly half of the total variation, and its importance remains stable over time. Second, the importance of firm premia declines, while worker–firm sorting remains quantitatively important. Thus, the decline in firm premia does not eliminate the importance of allocation across employers. Third, occupation effects recede in importance. Bias-corrected results based on firm clusters show a larger worker–firm correlation contribution, around 21%–22%, compared with about 12% in the baseline specification.

The paper also contributes to three related literatures beyond the GRID framework. First, it adds to research on income and wage inequality in Hungary. Recent administrative evidence shows that Hungarian wage inequality decreased during the 2010s, while total market-income inequality increased slightly, partly because of changes among marginally attached workers (Svraka, 2021). Earlier work on Hungarian wage inequality emphasizes technological change, educational expansion, and the minimum wage as central forces shaping the wage distribution before and after the transition period (Telegdy, 2018). Broader distributional evidence from WID also describes Hungary as a country with relatively moderate and stable income inequality over the past decade, but with substantially higher wealth concentration (World Inequality Database, 2026). Our contribution is to connect these broader structural and labor market patterns to harmonized evidence on earnings inequality and earnings volatility in Hungary. While previous studies have examined these dimensions separately, our paper provides a unified and detailed analysis within a consistent empirical framework using harmonized longitudinal data.

Second, the paper contributes to the AKM literature on wage inequality and employer heterogeneity. Since Abowd et al. (1999), linked employer–employee studies have shown that wage dispersion reflects not only persistent worker heterogeneity, but also employer wage premia and the sorting of workers across firms (Card et al., 2013, 2018; Torres et al., 2018; Song et al., 2019). We extend this approach by adding occupation effects and by asking whether Hungary's wage compression is reflected mainly in worker, firm, occupation, or sorting components. Including occupation effects is particularly important in the Hungarian context, where structural transformation, educational upgrading, and changes in the occupational composition may have played a central role in shaping wage inequality beyond worker and firm heterogeneity alone.

Third, the paper contributes to the literature on wage floors and earnings inequality. Recent studies show that minimum wages can compress the lower tail of the wage distribution and affect earnings inequality through wage spillovers and employment responses (Cengiz et al., 2019; Engbom and Moser, 2022; Dube and Lindner, 2024). We complement this literature by distinguishing between hourly wages and annual earnings. In the case of Hungary, we show that declining hourly-wage dispersion does not translate mechanically into lower annual earnings inequality, as part of the compression is offset by changes in labor-supply margins, especially contracted hours and employment intensity among low-wage workers.

The chapter proceeds as follows. Section 2 describes the data and institutional background. Section 3 presents harmonized facts on inequality, volatility, skewness/kurtosis, and mobility. Section 4 investigates the diverging wage and earnings dispersion patterns. Section 5 reports the AKM-based decomposition and interprets changes across periods. Section 6 concludes.

2. Data and institutional background

2.1. Institutional background

Hungary's earnings distribution over the past two decades has been shaped not only by macroeconomic cycles but also by changes in the institutional environment. To better understand the patterns of inequality, income instability, and mobility discussed in the following sections, it is useful to outline the main characteristics of the Hungarian labor market that underpin these developments.

Employment relationships in Hungary are governed by formal contracts that clearly define the mode of remuneration, distinguishing between hourly pay and fixed salaries. These contracts set the base wage, which employers generally cannot alter without the employee's consent. The dominant form of employment is full-time, salaried work, most commonly based on a standard 40-hour working week. Although the role of part-time employment has grown gradually since the early 2000s, it continues to represent a relatively small segment of the labor market, remaining below 20 percent overall (see Fig. 13). Within this category, very short-hour contracts—particularly those involving 20 h per week or less—are even less common, accounting for under 10 percent of total employment as of 2021 (see Fig. 13).

Employers retain the right to request overtime work, which is legally subject to additional compensation, though in practice, informal or unpaid overtime is not uncommon. Beyond base wages, compensation often includes variable components such as bonuses, performance-related pay, and fringe benefits, the level and structure of which are typically determined at the employer's discretion. Importantly, total monthly earnings must not fall below the contractually agreed base wage. On average, these flexible components constitute roughly one-tenth of total earnings in Hungary—a proportion broadly in line with Western European practices, though somewhat higher than observed in the United States.

Until 2010, Hungary had a progressive personal income tax system with multiple tax brackets. Between 2011 and 2013, this system underwent a major reform. In 2011, the government introduced a flat 16% personal income tax rate. However, because two transitional elements were still in effect,[1] the reform did not function as a fully flat tax immediately (Krekó et al., 2023). Only after these mechanisms were phased out by 2013 did Hungary's personal income tax system become truly single-rate in both structure and effect, with the flat rate decreasing to 15% in 2016. The reform also changed the structure of the family tax allowance. It

[1] Notably, the tax base credit (which provided relief mainly for low earners) and the so-called "super-grossing" system (which temporarily added employers' social contributions to the tax base, resulting in higher effective tax rates).

primarily benefited families with children, especially those in the middle- and higher-income ranges. As a result, the progressivity of the tax system decreased, leading to significant net income gains for higher earners, while low-income groups (unless they were eligible for certain allowances) often saw no reduction in their tax burden. Overall, the 2011–2012 tax reform represented one of the largest structural changes in Hungary's tax system, shifting the emphasis toward improving the net position of higher-income earners while reducing the overall level of income redistribution.

Until 2006, the country had a single national minimum wage. A major institutional reform introduced a two-tier system, consisting of a general minimum wage and a higher skilled minimum wage applicable to jobs requiring at least secondary education or vocational qualifications. Since then, both wage floors have increased, with particularly pronounced adjustments in 2012 and 2017 (see Fig. A.1). The sharp increase in 2012 was closely linked to broader tax reforms. Notably, the elimination of tax credits significantly reduced net earnings for low-wage workers. To offset this effect and prevent a decline in disposable income at the bottom of the wage distribution, the government implemented substantial minimum wage increases (European Central Bank, 2016). A second major increase in minimum wages occurred in 2017, following a comprehensive multi-year wage agreement concluded in late 2016 among the government, employers, and trade unions. The agreement introduced substantial increases in both the general and the skilled minimum wage, while simultaneously reducing employers' social contribution taxes from 27 to 22 percent, thereby offsetting part of the rise in labor costs for firms (Magyar Nemzeti Bank, 2017). This coordinated policy package emerged in a context of tightening labor market conditions and growing labor shortages, aiming to support faster wage growth, encourage labor supply, and reduce informal employment. During the second half of the 2010s, the statutory minimum wage amounted to roughly 38–40 percent of the average full-time wage. While this level is not exceptional compared to European or other OECD countries, the large and repeated increases in the minimum wage and the skilled minimum wage likely had a substantial influence on the lower part of the Hungarian wage distribution.

Although collective agreements exist in some larger firms and public institutions, wage setting remains largely decentralized. Wage negotiations typically take place at the individual or firm level. The statutory minimum wage nevertheless serves as an important benchmark, even in sectors where actual wages are higher. Overall, Hungarian wages display moderate downward flexibility by international standards (Kátay, 2011), with the minimum wage acting as the main constraint on wage reductions.

Two further structural factors are important for interpreting firm and occupational wage differences over this period. First, Hungary experienced a substantial expansion in educational attainment and in the supply of highly educated workers. Telegdy (2018) argues that the Hungarian wage structure since the transition was shaped by the interaction of technological change, educational expansion, and the minimum wage: rising demand for skilled labor and the rising minimum wage increased wages in some parts of the distribution, while the growing supply of graduates worked in the opposite direction.

Second, Hungary's accession to the European Union gradually changed outside options for Hungarian workers. Access to Austria's labor market did not open fully in 2004: Austria used transitional restrictions, introduced only limited openings for selected skilled occupations in the late 2000s, and removed the remaining restrictions for workers from the 2004 accession countries in 2011 (Eurofound, 2007; European Commission, 2011). This mattered especially in Western Hungary, where commuting to Austria became increasingly common. Szabó (2024) documents a sharp increase in Hungarians working in Austria after 2011, while Lindner et al. (2025) use the opening of the Austrian labor market as a natural experiment and find that it increased wages and reduced employment in the Hungarian border region.

In such an institutional setting, where the minimum wage constitutes a binding constraint in a largely decentralized wage-setting environment, increases in the minimum wage may not only raise formal labor costs but also influence firms' incentives to engage in informal wage arrangements (Bíró et al., 2021). Envelope wages—defined as situations in which formally employed workers receive part of their remuneration undeclared—are explicitly identified as a common form of undeclared work in Hungary by the European Labour Authority (European Labour Authority, 2023). Survey-based evidence from the European Commission Special Eurobarometer 498 indicates that approximately 4% of Hungarian employees reported receiving envelope wages in 2019 (European Commission, 2020), suggesting that the phenomenon affects a non-negligible minority of the workforce. At the same time, broader estimates of undeclared work—which include both fully undeclared activities and under-declared wages—show that the share of undeclared labor input in the private sector slightly decreased from 17% in 2013 to 16% in 2019, but was still above the EU-27 average (11%) (European Labour Authority, 2023).

It is worth noting that Hungary provides exceptionally long post-birth leave and benefit entitlements by international standards. Following childbirth, mothers (with stable previous employment) are entitled to 24 weeks of maternity leave, during which they receive the maternity allowance, typically amounting to 70% of their previous average earnings. After this period, eligible parents may claim the child care allowance until the child's second birthday, which also amounts to 70% of prior earnings up to a statutory cap. Once it expires, families can receive the universal flat-rate child care benefit until the child turns three.[2] These entitlements make Hungary's system one of the most generous in Europe in terms of duration and coverage.

Employment while receiving maternal-related benefits was historically restricted. The rules have gradually become more flexible. Hungarian labor law also provides strong job protection for mothers: dismissal is generally prohibited during pregnancy and parental leave, and women have the right to return to their previous position until the child's third birthday. In practice, these generous and lengthy entitlements encourage extended stays at home (Boza and Szabó-Morvai, 2025), with even single-child mothers often staying home for two or even three years after childbirth. Consequently, young women in Hungary may experience greater income volatility around childbirth compared to their peers in many Western European countries.

[2] However, this flat rate benefit is rather modest, as it has been lower than 100 EUR per month in this period.

Regarding the macroeconomic environment, Hungary experienced a deep and unusually prolonged downturn around the global financial crisis. The slowdown began before the international shock fully unfolded: after years of fiscal imbalance, post-2006 fiscal consolidation weakened domestic demand, and real GDP growth had already slowed markedly by 2007. The crisis then intensified in 2008–2009, when Hungary was hit by tightening external financing conditions, falling external demand, and a sharp contraction in investment and output. Real GDP fell steeply in 2009, while unemployment rose with a lag and remained elevated into the early 2010s (see Fig. A.2). This episode is therefore best interpreted as a multi-year macroeconomic downturn rather than a single-year shock.

A second recession occurred in 2012, before the recovery from the global financial crisis had fully consolidated. This downturn was milder in terms of output loss, but it came after several years of weak growth and high unemployment. It reflected a combination of weak European demand, constrained credit conditions, and domestic uncertainty, which together produced another contraction in real activity. In this sense, 2012 marks a renewed interruption in the recovery path rather than an isolated cyclical fluctuation.

The final major recessionary episode in our observation window is the COVID-19 shock in 2020. Unlike the post-2008 downturn, it was abrupt and largely driven by pandemic-related restrictions and sectoral disruptions. Output fell sharply, but the contraction was shorter-lived than the global-financial-crisis episode, followed by a relatively rapid rebound as restrictions eased and economic activity normalized.

These episodes provide the macroeconomic background for interpreting the Hungarian GRID statistics over time. Throughout the manuscript, we identify years as 'recessions' if at least one quarter registered a quarter-on-quarter real GDP fall of at least 0.5 percent; applied to quarterly GDP indices, this identifies 2007, 2008, 2009, 2012, and 2020 as recession years.

2.2. Dataset

We use the Linked Administrative Panel Database (Admin4) provided by the Databank of the ELTE Centre for Economic and Regional Studies (ELTE KRTK).[3] We rely on the fourth wave of the dataset (Admin4), which spans the period 2003–2022 and represents a substantial expansion in both scope and coverage relative to earlier versions. The database contains a 50% random sample of all individuals in Hungary with a social security number, corresponding to roughly six million people. The sampling is due to legal reasons, and happens on the level of individuals, providing a balanced panel. The dataset follows individuals over time, accounting for entries (births and immigration) and exits (deaths and deregistration), and includes all employers linked to the sampled individuals across both the private and public sectors.

The dataset is constructed by integrating administrative records from multiple government agencies, including the National Health Insurance Fund Manager (NEAK), the Hungarian State Treasury (MÁK), the Education Office (OH), the National Vocational and Adult Education Office (NFSZH), the former Ministry of Technology and Industry (TIM), and the National Tax and Customs Administration (NAV). Individual- and firm-level records are anonymized and merged into a unified database. Data processing is carried out centrally and results in spell-based administrative records which are subsequently transformed into a monthly panel structure. Individuals can be followed for up to 240 months, with detailed information on their labor market histories.

Employment information is based on employer-reported contribution records used for determining pension eligibility. These records cover both standard employment relationships and various non-standard arrangements, including public employment schemes, simplified employment contracts, and self-employment. Each employer is assigned a unique anonymous identifier, allowing the linkage of workers to firms. The data include key job characteristics such as contracted working hours, insured days within a month, and pension-contributory earnings. Occupations are coded according to the Hungarian Standard Classification of Occupations, harmonized with the ISCO framework. Multiple job holding is also observed: at any point in time, around 10% of workers have more than one concurrent employment spell.

Despite its richness, the dataset has several limitations that are important for interpretation. First, members of the armed forces (police and military) were recorded in a separate administrative system until 2012 and therefore do not appear as employed in the data; to maintain consistency, we exclude them throughout the sample period. Second, as is typical for administrative records, undeclared ("informal") employment is not captured. This is particularly relevant in the presence of "gray" wage practices, such as envelope-pay, where part of earnings may have been paid informally and thus not subject to contributions, leading to a downward bias in recorded income.

Further limitations arise from the structure of earnings reporting. The data only includes income subject to social security contributions. Pension contributions were subject to an upper cap until 2012, implying that reported earnings are censored at the contribution ceiling. As a result, the upper tail of the earnings distribution is top-coded—affecting roughly the top 5% of earners in 2003 and around 2% of earners in 2004–2011.

Finally, the reporting frequency has changed over time. Before 2012, most employers reported earnings on an annual basis, whereas monthly reporting became mandatory from 2012 onward. For the earlier period, monthly income profiles are constructed by interpolating annual earnings across active months. While this does not affect yearly aggregates, it introduces a structural break in the data around 2011–2012 that cannot be fully eliminated. Accordingly, the dataset is best interpreted as consisting of two periods (2004–2011 and 2012–2021), with the transition years requiring particular caution.

For those who have already entered the sample by 2021, the dataset contains employment records for 2022 as well. However, new immigrants arriving in 2022 are not part of the dataset, hence creating a slight change in data composition between 2021

[3] The Linked Administrative Panel Database (Admin) is the property of the data owners and their legal successors: NEAK, MÁK, NAV, ITM, and OH. The data used was processed by the Databank of the ELTE Centre for Economic and Regional Studies (ELTE KRTK).

and 2022. Therefore, we do not use data from 2022 for reporting the main moments corresponding to that year. Still, for earnings dynamics indicators (such as 1-year, 5-year changes), we can use information from this year as well, as the dataset is balanced until 2022 for those who have entered the Hungarian labor market by 2021.

2.3. Earnings and wage measures

We construct two complementary earnings measures from the administrative data: total annual earnings and an (approximate) hourly wage. Each captures different aspects of individuals' labor market outcomes. All monetary amounts are converted to 2018 Hungarian forints using the national consumer price index (CPI), ensuring that earnings are measured in real, constant-price terms.

Total annual earnings. Our main outcome variable is total annual earnings. We calculate this as the sum of all (monthly) earnings received within a given calendar year that are subject to social security contributions. This includes base pay, overtime payments, and both regular and non-regular bonuses. The measure aggregates income across all employment spells held by an individual, including both primary and secondary jobs within each month.

Given the presence of top-coding in the raw data prior to 2012, we harmonize the income measure across the full sample period. Specifically, we apply a 2.5% top winsorization to yearly earnings in all years. In addition, we exclude the year 2003 from the analysis, as the relatively low contribution ceiling in that year results in excessive censoring of the upper tail. While winsorization inevitably reduces variation at the top of the distribution, it allows for a consistent treatment of high-income observations and prevents artificial shifts in earnings dynamics induced by changes in reporting rules. Still, many moments presented through this study rely on percentile values of the earnings distribution (such as P10 and P90), and are therefore not or just partially affected by the winsorization.[4]

It is important to note that our income measure reflects only earnings that are officially declared and subject to contributions. As a result, it does not capture informal income components and may understate total earnings, particularly for certain groups such as the (partially) self-employed or individuals engaged in partially undeclared work.

Hourly wage (approximation). To obtain a measure that reflects underlying wage rates, we construct an approximate hourly wage variable using information on monthly earnings, days worked, and contracted weekly hours. It separates the price of labor (pay per hour) from employment intensity (hours and months worked). This distinction allows us to examine pay setting directly, without conflating it with variations in hours or employment spells.

The construction proceeds in two steps. First, monthly earnings are scaled to correspond to a full month of work. This adjustment corrects for partial months due to job entry or exit, as well as absences, by proportionally inflating observed earnings based on the number of insured (contracted) days in the given month. Second, the adjusted monthly earnings are divided by four times the reported weekly working hours. This yields a measure that accounts for differences between full-time and part-time employment. The top 2.5 percentiles of these monthly-level wage rates are also winsorized based on each year's joint wage distribution.

This variable should be interpreted as an approximation of the hourly wage. While it adjusts for contractual working time, it does not capture actual hours worked, which would include overtime, as they are not observed in the administrative data. As a result, the measure may deviate from true hourly wage rates, particularly in jobs with substantial overtime or irregular working hours. Still, adjusting for the number of contracted working hours is important for the wage analysis in the second half of the paper.

2.4. Sample selection

Following the conventions used in the GRID project, we restrict the dataset to individuals with a clear employment relationship and positive earnings reported by an employer. The analysis covers employees in both the private and public sectors, excluding self-employed individuals, entrepreneurs, and other non-wage earners. To remove marginal or incidental employment, we exclude all observations where annual earnings falls below one and a half months of full-time work at the statutory minimum wage (that is, the equivalent of three months of part-time employment). This lower earnings bound ensures that the sample represents workers with stable labor-market attachment. In addition, we limit the population to individuals aged 25 to 55 as of the reference year, thereby excluding students, retirees, and other non-active age groups.

The first part of the paper, which examines trends and dynamics in earnings inequality, relies on a yearly-level sample. In this dataset, earnings is defined as total gross annual earnings from all jobs held during the year. Individuals with zero or missing annual earnings are excluded, as such cases typically indicate periods without registered employment rather than valid low-earnings observations. For the main cross-sectional analysis, we use 2004–2021; for forward-looking earnings-dynamics measures, we also use 2022 records where required.

The second part of the paper, which focuses on wage equations, draws on a monthly sample. We retain the same sample definitions as before, including the 25–55 age range. However, we drop forms of employment where working hours are not explicitly recorded and, therefore, wage measures cannot be calculated. For a comparison of included employment types, see Table A.1.

[4] Because winsorization is applied to the pooled earnings distribution rather than separately within demographic groups, its impact differs across subpopulations. High-income men are overrepresented in the upper tail of the earnings distribution, implying that a larger share of male observations is affected by top-coding than the nominal 2.5 percent threshold, while the corresponding share is smaller among women.

Table 1
Main descriptives of the datasets used.

	Earnings data (annual)				Wage data (monthly)	
	2004	2010	2013	2019	2004–2010	2013–2019
Observations						
Total	1,447,749	1,416,495	1,445,013	1,495,049	88,388,885	86,627,649
Male	723,368	730,220	736,477	769,311	43,709,034	43,852,779
Female	724,381	686,275	708,536	725,738	44,679,851	42,774,870
Average age						
Total	38.6	38.9	39.1	39.8	40.2	40.7
Male	37.9	38.3	38.6	39.3	39.5	40.1
Female	39.2	39.5	39.5	40.3	40.9	41.3
Log earnings | log wage						
Total	14.24	14.23	14.27	14.75	7.10	7.35
Male	14.25	14.24	14.30	14.81	7.12	7.40
Female	14.23	14.22	14.24	14.69	7.07	7.30

Notes. The table reports descriptive statistics for the samples used in the analysis. The left panel is based on an annual dataset, where each individual contributes one observation per year. It includes employees in the private and public sectors with positive employer-reported earnings, excluding the self-employed and other non-wage earners. Annual earnings is defined as total gross earnings across all jobs. Observations with zero or missing income are dropped, as are those with earnings below the equivalent of 1.5 months of full-time minimum wage. The sample is further restricted to individuals aged 25–55. The right panel is based on a monthly dataset used to estimate multi-way wage equations over two seven-year periods. In addition to the above restrictions, we exclude employment types without recorded working hours, as wage measures cannot be constructed for these cases. See Table A.1 for details on employment categories.

For our wage analysis, this dataset is split into two periods: 2004–2010 and 2013–2019. To avoid specific changes in data reporting, we exclude the years 2011 and 2012. By excluding years 2020 onwards, we remove disruptions related to the COVID-19 pandemic, and can focus on two same-length periods that are representative of their corresponding decades.

Table 1 presents some basic descriptive statistics of our samples. The first four columns show descriptions for selected years used in our annual earnings analysis, in which each person contributes one observation per year. The last two columns are from the monthly dataset that we use for estimating multi-way wage equations on two separate time periods of seven years each.

Male and female employees are presented in both samples at roughly the same ratio. Male workers are somewhat younger in both of the samples, but they earn higher wages on average. The gender gap in both earnings and wages is present, especially in the later periods of the data. An increase in (real) earnings is apparent in the second half of the observation period.

3. Earnings inequality and dynamics in Hungary

We present descriptive evidence on income inequality, volatility, and mobility in Hungary. We begin by documenting changes in earnings inequality between 2004 and 2021. In the core of the paper, we present the results separately for men and women.

3.1. The earnings distribution in Hungary

Fig. 1 presents the distribution of log annual gross earnings in the beginning (2004) and end (2021) of our main observation period.

In 2004, the distribution of annual gross earnings in Hungary (expressed in 2018 HUF) exhibited pronounced inequality within both genders. Among women, the 10th percentile of the log earnings distribution stood at 13.13 (∼504,000 HUF per year), while the 90th percentile reached 15.20 (∼3.99 million HUF), indicating that top earners made roughly eight times more than those at the bottom. The average log earnings for women were 14.23 (∼1.51 million HUF), reflecting a right-skewed distribution with a long upper tail. Among men, the corresponding values were 13.13 (∼504,000 HUF) at the 10th percentile and 15.37 (∼4.73 million HUF) at the 90th percentile, with an average of 14.25 (∼1.54 million HUF). These figures suggest a similar degree of within-gender inequality for men and women, with roughly an eight- to ninefold difference between low and high earners.

In the top panels, the influence of the statutory minimum wage is clearly reflected in bunching around its annual value. However, because here we analyze annual earnings rather than monthly earnings or wages, the minimum does not operate as a perfectly binding threshold. While we observe clear bunching around the annualized minimum wage, there is also a substantial mass below it, reflecting partial-year employment, part-time contracts, or employment transitions over the year (e.g., mothers moving to or returning from parental leave). Among women (and to a small extent, also among men), a secondary mode emerges around half of the annual minimum wage, consistent with part-time work.[5]

In the bottom panels, bunching is present both near the minimum wage and even more so near the skilled wage minimum, with additional spikes corresponding to part-time equivalents of both thresholds. Taken together, these features indicate that adjustments

[5] The figures also tell us that winsorization at the top of the distribution affects a larger share of men than women, reflecting a higher share of men among high-earners.

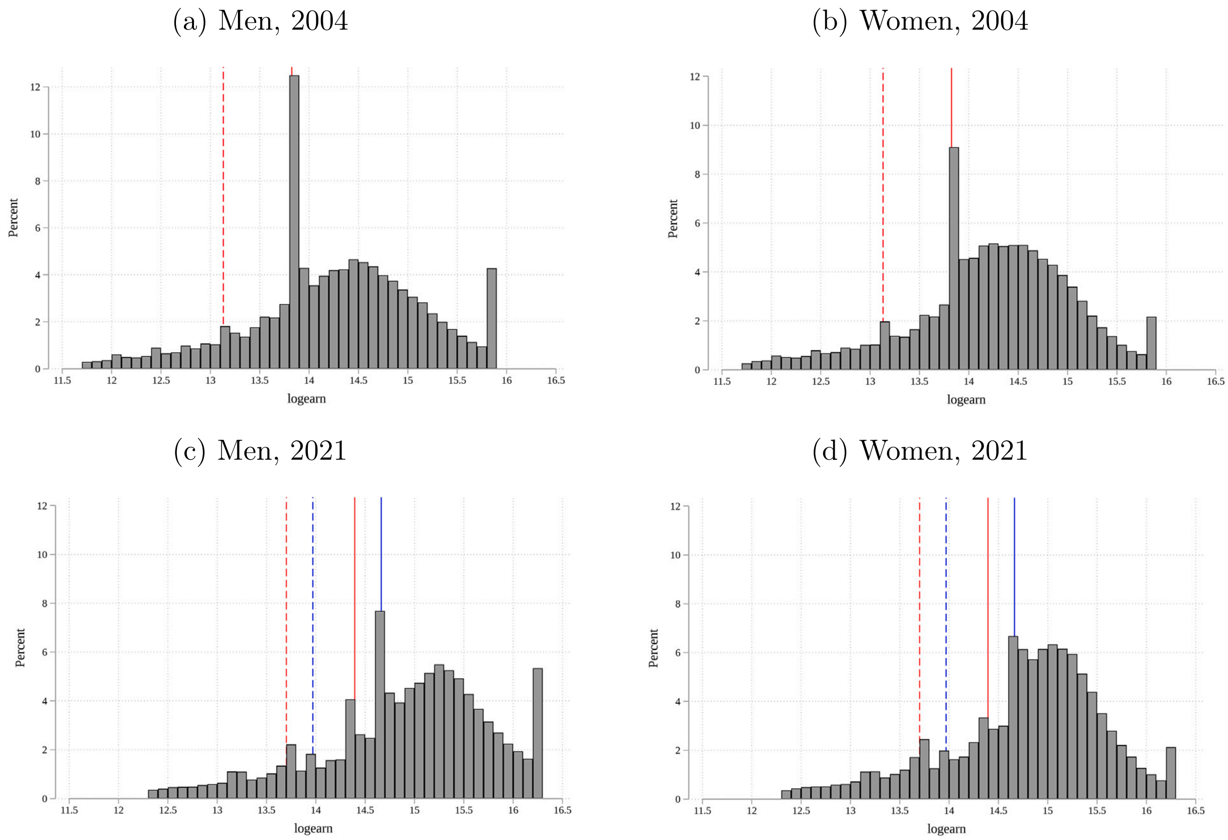

Fig. 1. Earnings distributions in 2004 and 2021.
Notes. The figure shows distributions of log annual earnings for men and women in 2004 and 2021, using bins of width 0.1 log points. The solid red vertical lines mark the log value of 12 months of the statutory minimum wage and, where applicable, solid blue lines mark 12 months of the skilled minimum wage. The dashed lines mark the corresponding values for 6 months of the minimum wage (red) and skilled minimum wage (blue), respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

to the minimum wage in Hungary tend to influence the lower half of the earnings distribution substantially. In Fig. A.3 we plot the percentiles of the annual (real) earnings distribution across the whole period, along with the (real) minimum wage level. The upward shift in real earnings in the 2010s is apparent along the whole earnings distribution, but is seemingly stronger in the lower tail.

3.2. *Evolution of inequality*

3.2.1. *Evolution of annual earnings inequality*

Fig. 2 plots log real income percentiles relative to 2004, with panels (a) and (b) displaying percentiles up to the 90th by gender.

Earnings increased steadily until 2007, followed by a period of stagnation and modest decline during the 2008–2010 recession, with the 10th percentile experiencing a particularly sharp drop after 2007. The economic downturn affected men more severely than women. From 2012 onward, earnings rose markedly, reflecting both macroeconomic recovery and institutional changes (e.g., minimum wage adjustments, see Section 2.1).

The figures suggest that earnings growth over the period was concentrated around the median. By 2021, median real earnings were approximately 80 log points higher for men and 60 log points higher for women than in 2004, with men consistently experiencing larger gains than women, implying a widening gender gap in median earnings.

Panels (c) and (d) of Fig. 2 show the evolution of log incomes at the upper end of the earnings distribution, going up to the 97.5th percentile. The upper tail of the distribution exhibits a pattern broadly similar to the rest: earnings remained relatively stable until 2011, followed by a sharp and sustained increase from 2012.[6] Taking a closer look at inequality dynamics, Fig. 3 illustrates the

[6] However, the interpretation of the highest reported male percentiles should be made with some caution, as top-coding affects a larger share of male observations than implied by the overall 97.5th-percentile threshold. This may also influence the evolution of the highest reported male percentiles.

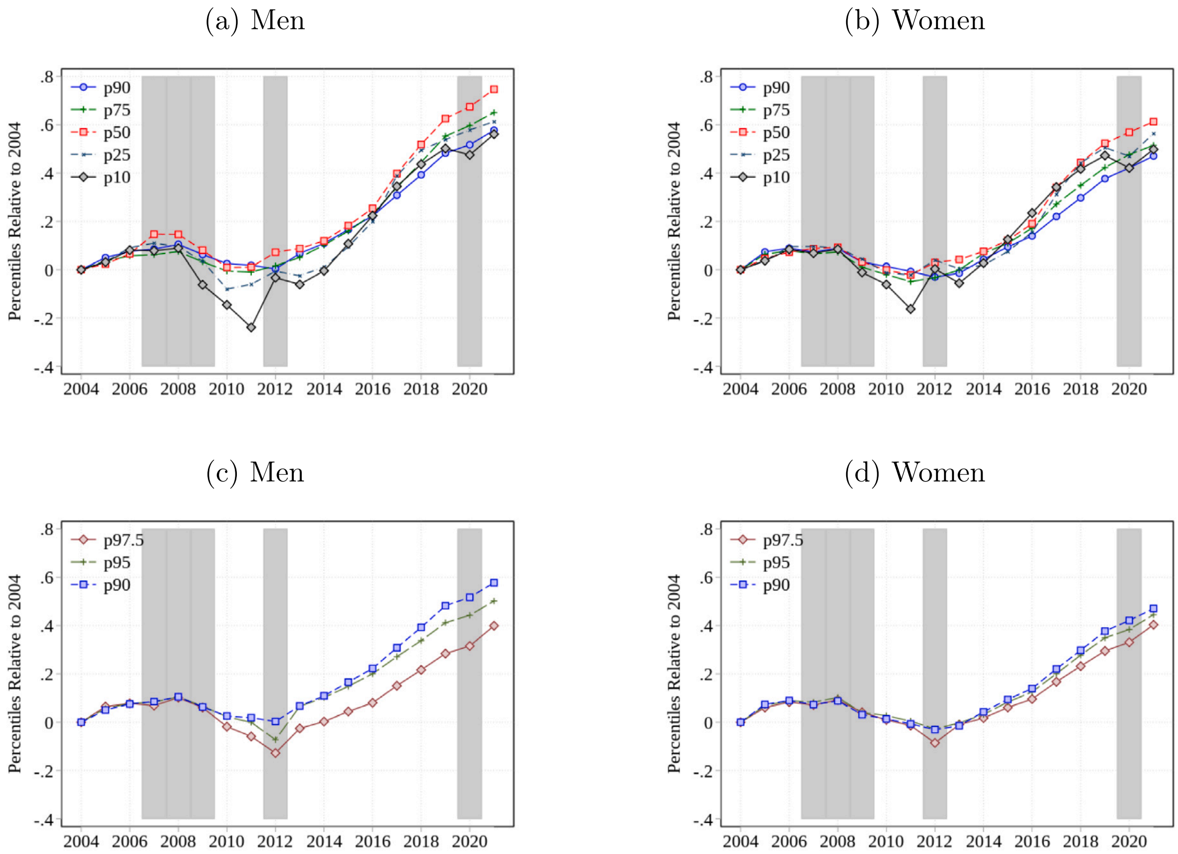

Fig. 2. Change of percentiles of the log real earnings distribution.
Notes. This figure shows the change in selected percentiles of the cross-sectional distribution of log real labor earnings relative to their 2004 values by gender. Shaded areas indicate recession periods. Because earnings in Hungary were top-coded at approximately the 98th percentile until 2012, we winsorize earnings at the 97.5th percentile of the annual earnings distributions. Accordingly, we do not report finer detail above this threshold.

evolution of different measures of income inequality over time. Panels (a) and (b) show the standard deviation and the difference between the 90th and 10th percentiles in log earnings by gender.

The figure indicates that the P90–P10 ratio for men followed a hump-shaped trajectory over the period, starting at around 2.25 in 2004, rising sharply to a peak of roughly 2.5 around 2011–2012, and then retreating to approximately 2.25–2.3 by 2021. At its peak, a 90th-percentile worker earned over 12 times ($e^{2.5}$) the income of a 10th-percentile worker, compared to roughly 9.5 times ($e^{2.25}$) at the start and end of the period. Women show a similar hump-shaped pattern but at a consistently lower level of dispersion, with the P90–P10 ratio peaking at around 2.20 in 2011 before declining to roughly 2.00–2.05 by 2021. Notably, for women, the P90–P10 ratio and the 2.56σ measure track each other closely throughout.

Compared to other GRID countries, Hungary sits at the high end of the earnings inequality distribution. Its P90–P10 ratio for both men and women is higher than most of the first-wave European GRID countries (Leth-Petersen and Sæverud, 2022; Friedrich et al., 2022; Bell et al., 2022; Halvorsen et al., 2022; Kramarz et al., 2022; Drechsel-Grau et al., 2022; Hoffmann et al., 2022), with only Spain recording higher earnings dispersion (Arellano et al., 2022). Hungary also exceeds Canada (Bowlus et al., 2022), though it falls below the United States (McKinney et al., 2022) and the Latin American GRID countries (Puggioni et al., 2022; Blanco et al., 2022; Engbom et al., 2022).

Panels (c) and (d) of Fig. 3 decompose the P90–P10 differential into "top inequality" (P90–P50 percentile gap) and "bottom inequality" (P50–P10 percentile gap). For men, bottom inequality widened until 2011, pushed by the collapse of 10th-percentile earnings during the 2007–2009 recession (Fig. 2). This gap then stabilized before rising again after 2016. Men's top inequality, by contrast, held steady until 2016 and then declined modestly through 2021. Women's inequality followed a different path until 2016, remaining stable in both halves of the distribution. After 2016, however, the female trends converged with the male trends: top inequality fell while bottom inequality rose.

We note that the skilled minimum wage increased sharply in Hungary relative to the general minimum wage in both 2017 and 2018 (see Fig. A.1), which widens inequality at the bottom of the distribution for both men and women. The skilled minimum wage

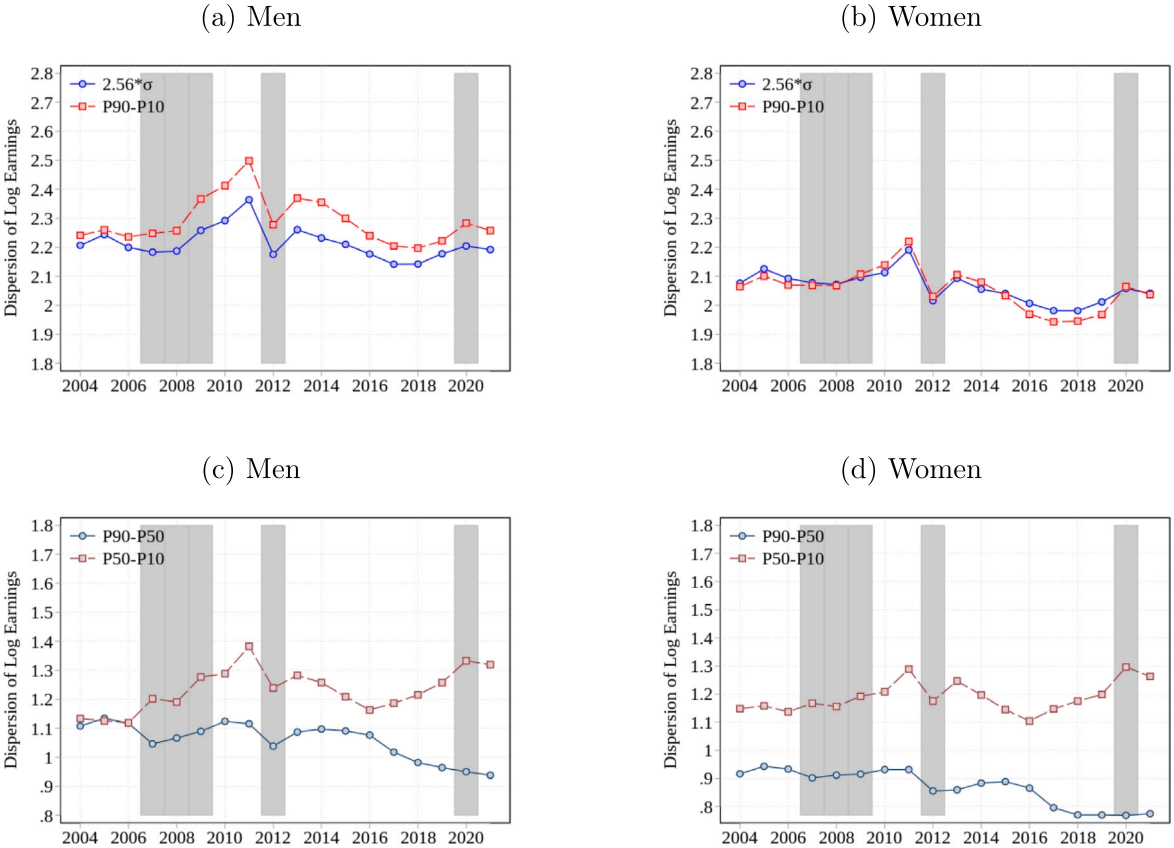

Fig. 3. Income inequality.
Notes. This figure shows the evolution of earnings inequality by gender. Panels (a) and (b) report two measures: 2.56 times the standard deviation and the P90–P10 difference in log earnings. Panels (c) and (d) decompose the P90–P10 difference into its upper (P90–P50) and lower (P50–P10) components. Shaded areas indicate recession periods.

pushed up earnings near the median, while the general minimum wage was closer to the 10th percentile, so the gap between them grew.[7]

Fig. 4 presents the same measures of top and bottom inequality, restricted to workers aged 25. The distributions and their evolution are remarkably similar for men and women at this age. Earnings among young workers have become increasingly unequal at the lower end of the distribution, even as disparities at the top have narrowed.

Overall, the results suggest modest increases in earnings inequality over the two decades. Hungary looks much like the group of countries in the first GRID wave (Guvenen et al., 2022) where overall inequality barely moved. France (Kramarz et al., 2022), Canada (Bowlus et al., 2022), the UK (Bell et al., 2022) and the US (McKinney et al., 2022), and the Nordic countries of Denmark (Leth-Petersen and Sæverud, 2022), Norway (Halvorsen et al., 2022), and Sweden (Friedrich et al., 2022) all tell a similar story. Hungary differs from other countries within this group as its modest rise in overall inequality hides two opposing forces. Inequality at the bottom went up while inequality at the top came down. No other country in the group shows this pattern, but Norway (Halvorsen et al., 2022) comes closest, with small increases at both ends.

3.2.2. Stable earnings dispersion and the rising minimum wage

The stable or only slightly increasing dispersion of earnings, especially at the bottom of the distribution, is somewhat surprising in light of the steady rise in the minimum wage over the period. A higher minimum wage would typically be expected to compress the distribution of wage rates and, through this channel, reduce dispersion in earnings as well.

Consistent with this intuition, Fig. 5 shows that the dispersion of hourly wages did in fact decline over time, particularly in years with large increases in either the general or the skilled minimum wage (illustrated on Fig. A.1).[8] The first notable drop

[7] Fig. A.3 plots the percentiles of the real wage distribution over the full period alongside the real log minimum wage, and tells the same story: the relative positions of the lowest percentiles changed little.

[8] Fig. 5 uses the monthly-level wage data, which excludes employment types where contracted hours data is not available and hence around 5% of monthly work observations (Table A.1). The overall annual earnings dispersion patterns are reassuringly similar on this slightly smaller sample as well.

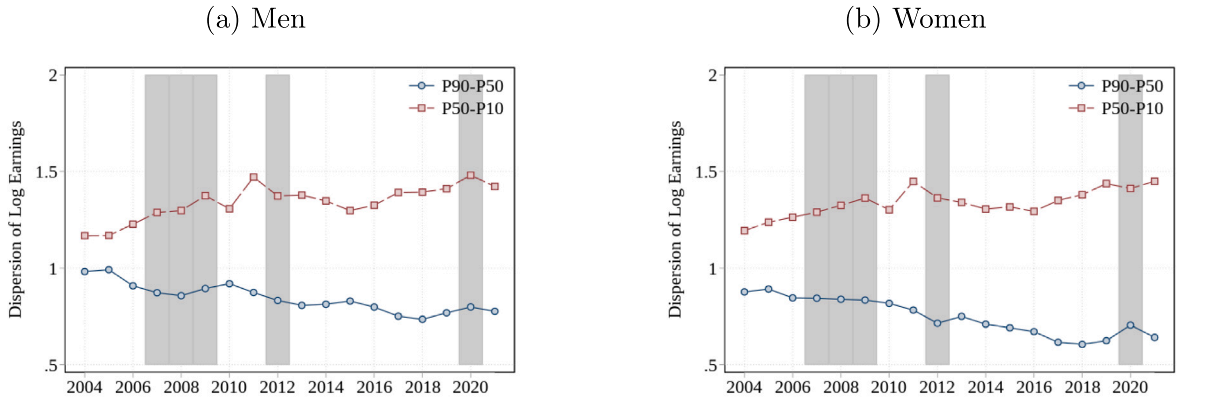

Fig. 4. Income inequality at age 25.
Notes. This figure shows the upper (P90–P50) and lower (P50–P10) components of the P90–P10 difference in log earnings at age 25 by gender. Shaded areas are recessions.

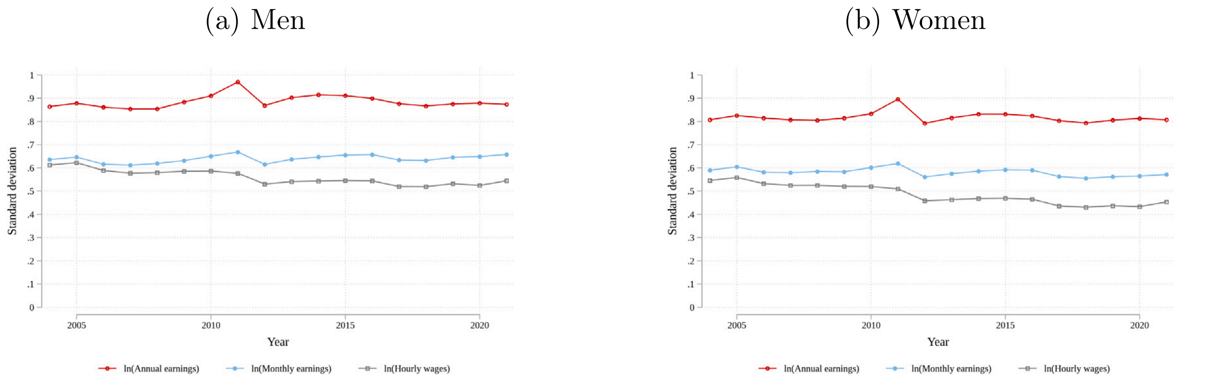

Fig. 5. Trends of earnings and wage dispersion.
Notes. This figure shows the evolution of the standard deviation of log annual earnings, log monthly earnings, and log hourly wages. The sample used is the subset of the main dataset where hourly wages could be estimated, i.e., individuals working in standard forms of employment.

occurred in 2006, when the government introduced the skilled minimum wage. Since this higher tier was set substantially above the general minimum wage, it effectively raised the wage floor for a large group of workers, leading to a compression of hourly wages between 2005 and 2006. A second pronounced decline in hourly wage dispersion is observed between 2011 and 2012, when the general minimum wage increased by almost 20% and the skilled minimum wage by around 15%. Finally, the sharp increases in 2017—approximately 15% for the general minimum wage and 25% for the skilled minimum wage—are again associated with a visible compression in the distribution of hourly wages. Overall, these episodes are consistent with a strong equalizing role of minimum-wage policy for wage rates.

In contrast, the dispersion of monthly earnings remained broadly stable over the same period. The divergence between hourly wages and monthly earnings points to an important role for variation in working time. In particular, it suggests that dispersion in hours worked increased, offsetting the compression in wage rates. Even if hourly wages become more equal, differences in the number of hours worked within a month can sustain, or even widen, dispersion in monthly earnings.

The comparison with annual earnings further reinforces this interpretation. The relative stability of monthly earnings, combined with the rise and subsequent decline in annual earnings dispersion documented earlier, indicates that variation in the number of days or months worked over the year also plays a role. This includes both short-term fluctuations in employment and longer interruptions, which affect annual income more strongly than monthly outcomes.

Taken together, these patterns highlight that earnings inequality cannot be understood from wage rates alone. Changes in labor supply (both in terms of hours worked within a month and employment over the year) are a key part of the story. In Section 4, we formally decompose earnings variation into wage and labor supply components to provide a more detailed account of these mechanisms.

3.2.3. Inequality over the life cycle

Before turning to income dynamics, we examine how earnings inequality evolves over the life cycle across cohorts. Fig. 6 plots the P90–P10 log earnings gap for four cohorts as they age: workers who were 25 years old in 2004, 2008, 2012, and 2016. The

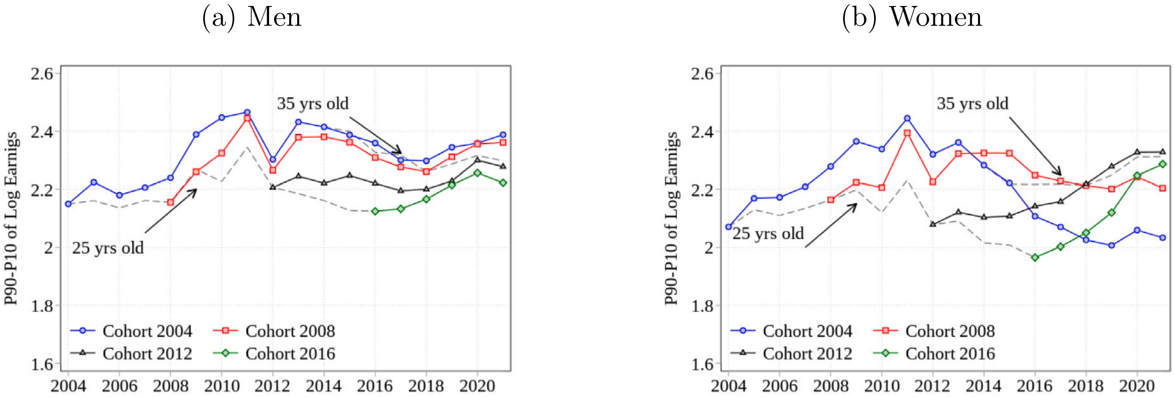

Fig. 6. Life-cycle inequality over cohorts.
Notes. This figure shows earnings inequality, measured by the P90–P10 log earnings differential, over the life cycle across entry cohorts and by gender. A cohort is defined by the year in which the cohort turns 25. Dashed lines connect individuals of the same age.

gray dashed lines trace inequality at fixed ages, 25 and 35, over time, which helps separate differences associated with age from those associated with cohort timing.

The figure reveals marked gender differences in life-cycle inequality profiles. Among men, inequality is relatively stable across cohorts and rises only modestly with age. There are almost no differences between cohorts, and the dashed age profiles suggest little change over time at age 35, but a slight increase in inequality at age 25. Among women, by contrast, both the level of inequality at younger ages and the subsequent age profile vary across cohorts. The dashed line at age 25 suggests declining inequality over time, while the cohort profiles diverge substantially at later ages. In the 2004 and 2008 cohorts, inequality declines after the early thirties, whereas this decline is absent in the 2012 and 2016 cohorts

These patterns are suggestive of cohort-specific changes in women's attachment to the labor market over the family-formation years. For earlier cohorts, the decline in inequality is consistent with stronger selection into labor-force exit in the early thirties, plausibly concentrated among more educated and higher-earning women, with the effect of compressing the earnings distribution. For later cohorts, the disappearance of this pattern is likewise consistent with a weakening of that selection mechanism, perhaps owing to the postponement of fertility among more recent cohorts (Lazzari et al., 2025).

3.3. Volatility, skewness, and kurtosis

After examining overall inequality, we now turn to the dynamics of individual earnings. To this end, we use residual log earnings, denoted by ε_{it}. Specifically, ε_{it} represents the residual from regressions of log real earnings on a full set of age dummies, estimated separately by gender and year. By focusing on changes in residual earnings, specifically, the log difference between consecutive years, $g_t^1 = \varepsilon_{t+1} - \varepsilon_t$, we remove systematic gender- and age-specific components and isolate idiosyncratic, year-to-year earnings growth at the individual level.

Fig. 7 plots one-year earnings growth volatility, split into right-tail (P90–P50) and left-tail (P50–P10) dispersion. For men, right-tail dispersion exceeds left-tail dispersion in most years. During the 2007–2009 recession and the COVID shock, this pattern reversed: the left tail widened sharply while the right tail compressed, consistent with large negative earnings changes becoming more common while large gains became rarer. For women, the two tails track each other more closely throughout, though the recessionary spike in left-tail dispersion is similarly pronounced. After the 2007–2009 crisis, right-tail volatility among men drifted downward through the mid to late 2010s, suggesting a secular compression of upside earnings dynamics beyond the cyclical recovery. For women, both tails returned to pre-recession levels with no comparable trend. This counter-cyclical left tail and pro-cyclical right tail mirrors what the first GRID wave found across many countries (Blanco et al., 2022; Engbom et al., 2022; Bowlus et al., 2022; Leth-Petersen and Sæverud, 2022; Kramarz et al., 2022; Hoffmann et al., 2022; Puggioni et al., 2022; Arellano et al., 2022; Friedrich et al., 2022; Bell et al., 2022; McKinney et al., 2022).

To further characterize these changes, we next examine how the overall shape of the earnings growth distribution evolves. Fig. 8 plots two distributional statistics: panel (a) shows Kelley skewness and panel (b) shows excess Crow-Siddiqui kurtosis of one-year residual earnings changes. Both measures are percentile-based and robust to extreme values. Skewness evolves similarly for men and women, with the two series running nearly parallel throughout the sample. It is strongly procyclical, falling sharply during recessions for both genders, as the left tail widens and the right tail narrows. This confirms that downturns are associated with a systematic shift of the distribution toward negative outcomes, consistent with evidence from Denmark (Leth-Petersen and Sæverud, 2022), Germany (Drechsel-Grau et al., 2022), and Sweden (Friedrich et al., 2022) found in the first GRID wave.

Kurtosis, by contrast, reveals important gender differences in the incidence of extreme earnings changes. Before the 2007–2009 recession, men exhibited substantially lower kurtosis, indicating fewer extreme earnings fluctuations and a less heavy-tailed earnings-growth distribution. During and after the recession, however, these differences narrow as the distributions converge. At the same

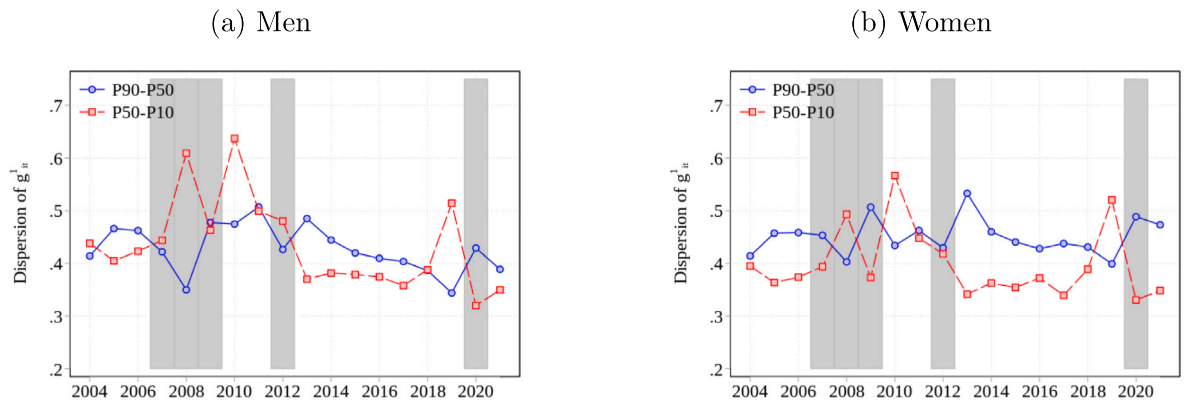

Fig. 7. Dispersion of 1-year log earnings changes.
Notes. This figure shows the dispersion of one-year log earnings growth by gender, broken down into the upper (P90–P50) and lower (P50–P10) components of the P90–P10 differential. Shaded areas are recessions.

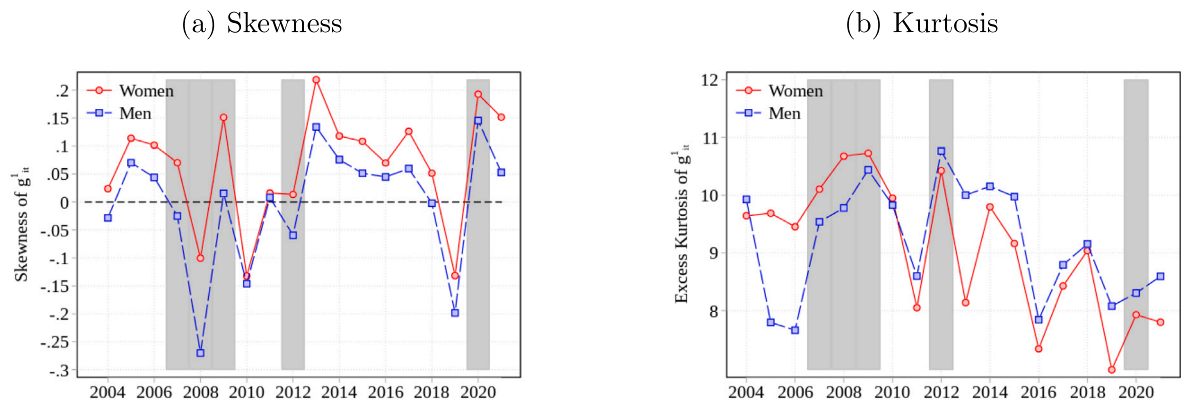

Fig. 8. Skewness and kurtosis of 1-year log earnings changes.
Notes. This figure shows the skewness and kurtosis of one-year log earnings growth by gender. Shaded areas are recessions.

time, women's kurtosis remains more volatile over time, pointing to greater instability in the distribution of their earnings growth. Taken together, these results suggest that business cycles not only affect the dispersion of earnings changes but also reshape the balance and extremity of risks, with slightly distinct implications across gender groups.

Gender differences in earnings dynamics may also vary systematically over the life-cycle and across the income distribution. To explore these dimensions, we compute permanent earnings by regressing the log of average earnings between years $t-2$ and t on a full set of gender- and year-specific age dummies, taking the residual, and adding back the raw sample mean. Fig. 9 displays the dispersion, Kelley skewness, and excess Crow–Siddiqui kurtosis of one-year earnings growth by gender, age group, and permanent income percentile. To make the figures easier to read, we truncate them at the 95th percentile, where mechanically large kurtosis values would otherwise distort the picture.[9]

Panels (a) and (b) of Fig. 9 show that earnings dispersion falls steeply below the 30th percentile and flattens above it, for both men and women and across age groups. Earnings risk is concentrated at the bottom, among workers with temporary contracts, unstable employment, and little bargaining power—not spread evenly across the distribution. That the pattern holds across age groups suggests it is structural, not a life-cycle artifact. The main exception is young women aged 25–34, who show markedly higher dispersion than older women or young men of the same age. As they age, their earnings paths stabilize, pointing to a temporary but sharply concentrated burst of instability in early career, likely tied to family formation, parental leave, and part-time transitions. These patterns are consistent with evidence from Northern and Western European countries (Leth-Petersen and Sæverud, 2022; Kramarz et al., 2022; Drechsel-Grau et al., 2022; Halvorsen et al., 2022; Friedrich et al., 2022).

Turning to panels (c) and (d), men's earnings growth is positively skewed across almost all percentiles, marginally more so below the 30th percentile, and turns negative at the top only for middle-aged and older workers. Women follow a broadly similar shape

[9] The source of such extreme kurtosis values is the winsorization of top values. As Fig. 1 suggests, almost 5% of male workers (and around 2% of female workers) are affected by the earnings cap we implement in the dataset.

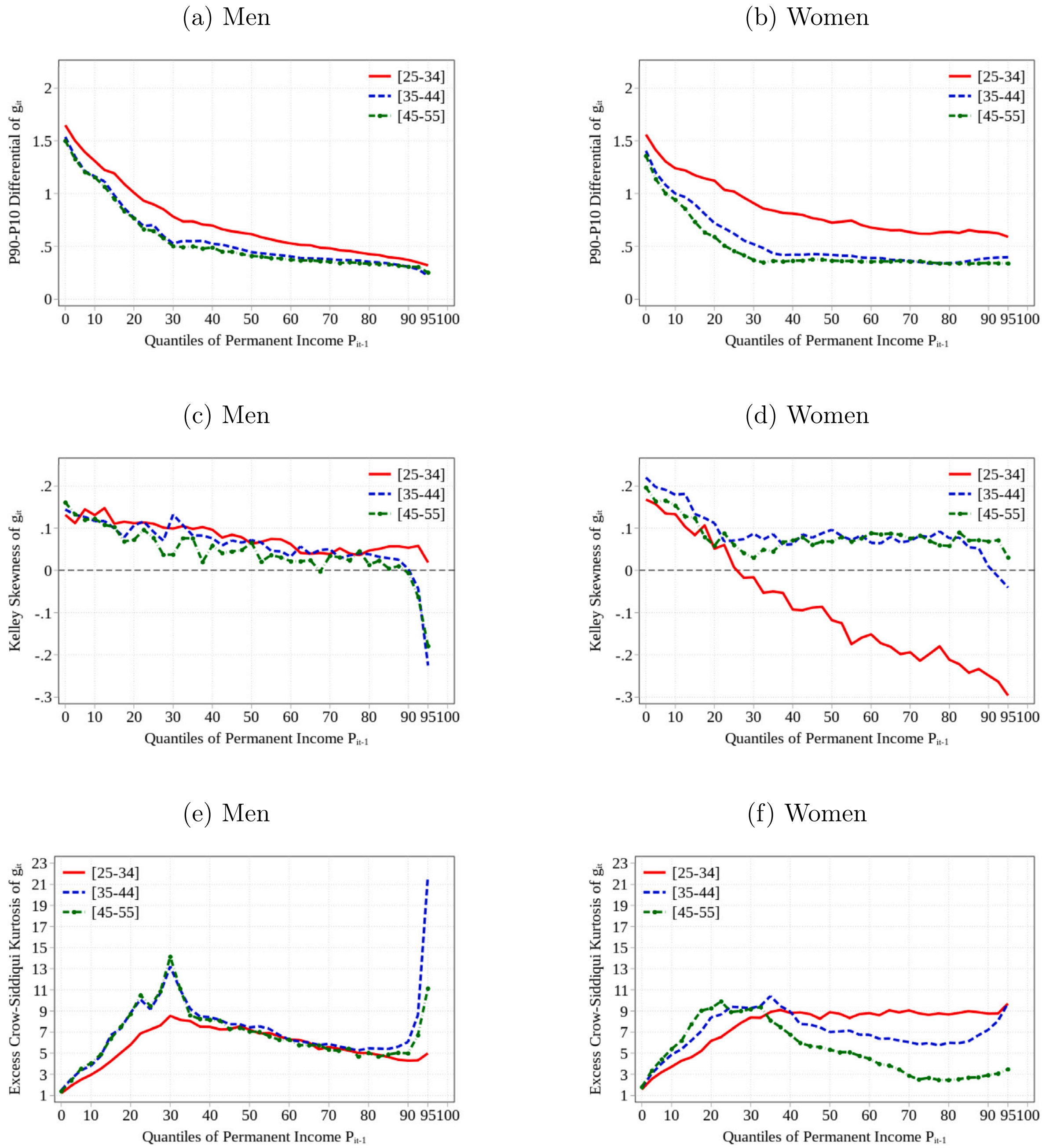

Fig. 9. Dispersion, Kelley skewness and Excess Crow-Siddiqui kurtosis of one-year log earnings changes by age Group.
Notes. This figure shows heterogeneity in log earnings growth across quantiles of the permanent income distribution, by age and gender. Panels (a) and (b) present the P90–P10 differential. Panels (c) and (d) show Kelley's skewness. Panels (e) and (f) display excess Crow–Siddiqui kurtosis.

but with more pronounced positive skewness below the 30th percentile. For both genders, positive skewness at the bottom and middle of the distribution implies that large upward earnings movements are more likely than large losses, suggesting the presence of upward mobility opportunities even among lower-income workers.

Negative skewness appears only around the 90th percentile and only for workers aged 35–44, with one striking exception. Young women show heavily negative skewness above the 30th percentile, meaning that for this group, large earnings changes are more likely to be losses than gains. This reflects asymmetric adjustment mechanisms: rather than gradual changes, women in this group are more likely to experience discrete negative shocks, such as reductions in working hours or exits from full-time employment. Childbearing provides a natural explanation for this asymmetry. A woman who gives birth partway through the year has no wage earnings for the remaining months, and possibly the whole following year. This gap hits harder higher up the distribution, where the difference between a full year of earnings and a partial one is largest. Transitions into part-time work after returning add a second, separate source of downward adjustment.

The Crow–Siddiqui kurtosis in the last row of Fig. 9 tells a consistent story at the bottom but reveals important differences further up. Both men and women exhibit rising kurtosis up to the 30th percentile, indicating that low earners face not only higher volatility but also a greater likelihood of extreme earnings changes. This suggests that income instability at the bottom is driven by substantial shocks, consistent with unstable employment relationships and exposure to job loss.

Interestingly, younger workers display lower kurtosis in this segment, implying that while their earnings may fluctuate, extreme events are somewhat less frequent, possibly reflecting shorter job tenures or more frequent but smaller adjustments.

Above the 30th percentile, however, the pattern reverses, and kurtosis increases steadily with permanent income. Among men, this increase becomes particularly pronounced near the top of the distribution. An important caveat is that this upper-tail pattern is likely influenced by top-coding. At very high permanent-income levels, many earnings changes are mechanically compressed because earnings remain within the top-coded region from one year to the next. As a result, a large share of observations record little or no measured earnings change even when underlying earnings fluctuate. This creates a concentration of observations around zero earnings growth and reduces the interquartile range appearing in the denominator of the Crow–Siddiqui kurtosis measure, mechanically inflating the kurtosis statistic. Consequently, the sharp increase in kurtosis among top-income men should not necessarily be interpreted as evidence of unusually large earnings shocks, but partly as a consequence of the way top-coding affects measured earnings dynamics near the top of the distribution. Because top-coding is defined on the pooled earnings distribution rather than separately by sex, its effects may also emerge for the male subpopulation at percentile ranks below the nominal 97.5th-percentile threshold. Men are disproportionately represented among top earners, implying that top-coding may already influence the highest reported portions of the profile, including observations around the 95th percentile.

For women, age drives the difference. Young women's kurtosis stays flat above the 30th percentile, meaning they face persistently fat-tailed shocks throughout the upper distribution. Women aged 35 to 44 and 45 to 55 follow a different path, with kurtosis declining until around the 80th percentile, rising again for the 35 to 44 group, and remaining flat for the oldest group. This means that between the 30th and 80th percentiles, older women experience comparatively moderate earnings changes, pointing to lower short-term earnings risk in this segment of the distribution and more stable, predictable earnings trajectories after the family formation stage. For young women the flat kurtosis above the 30th percentile, combined with the heavily negative skewness shown earlier, means their earnings shocks are not only more likely to be losses but more likely to be large losses. Which is consistent with women leaving for maternity leave at this age, losing all (wage) earnings from one-year to the next.

Taken together, these findings show that earnings risk in Hungary is strongly structured by both gender and position in the earnings distribution. Men's earnings dynamics are relatively stable and symmetric, with limited variation over the life cycle. Women face higher and more variable (wage) earnings risk, concentrated in the prime working ages. The asymmetric skewness patterns reinforce this picture. Women face greater exposure to downward shocks at higher earnings levels, while men's earnings changes are more evenly distributed. This is consistent with the findings of Boza and Szabó-Morvai (2025), who document strong child penalty effects for mothers, especially younger ones, and find that the probability of working part time more than doubles three years after the birth of a first child. Career interruptions and shifts in labor supply during family formation likely drive much of the elevated earnings risk among young and middle-aged women.

3.4. Mobility

We conclude this section by analyzing individual earnings mobility over a ten-year horizon and its evolution across the sample period. Fig. 10 plots the ten-year mobility rate by age and gender, defined as the average percentile an individual reaches ten years later against their initial position in the permanent earnings distribution. Using permanent earnings mitigates mechanical mean reversion effects and provides a cleaner measure of true mobility. The dashed black line marks the benchmark of zero mobility, which would be the outcome expected if individuals maintained their exact relative position in the distribution.

Mobility concentrates at the lower end of the distribution for both men and women, up to the 40th percentile. This pattern reflects a combination of upward mobility and mean reversion, which is commonly observed in earnings dynamics: individuals starting from low initial positions tend to move closer to the center of the distribution over time. Conversely, mobility is more limited toward the top, where there is less scope for further upward movement by construction and where downward adjustment partly reflects regression toward the mean rather than barriers to advancement.

There are, however, important gender and life-cycle differences. Younger and middle-aged women move up more than older women do, suggesting that early- and mid-career women have more room to advance. This likely reflects a combination of labor market entry, job-to-job transitions, and recovery from earlier career interruptions. Men show no such age gradient, as mobility is roughly the same across age groups, pointing to more uniform transitions over the life cycle. Women at the lower end of the earnings distribution therefore face more dynamic wage trajectories than men do, likely reflecting both higher turnover at labor market entry and catch-up after career interruptions.

Fig. 11 repeats the ten-year mobility measures for 2006, and 2011. Mobility changed little between these years for either gender, so the structure of short-term earnings transitions proved stable even through the global financial crisis and the recovery that followed. The combination of stronger upward mobility at the bottom and limited scope for upward movement at the top is also consistent with evidence from other GRID countries (Guvenen et al., 2022) and reflects a general tendency toward partial mean reversion in earnings distributions.

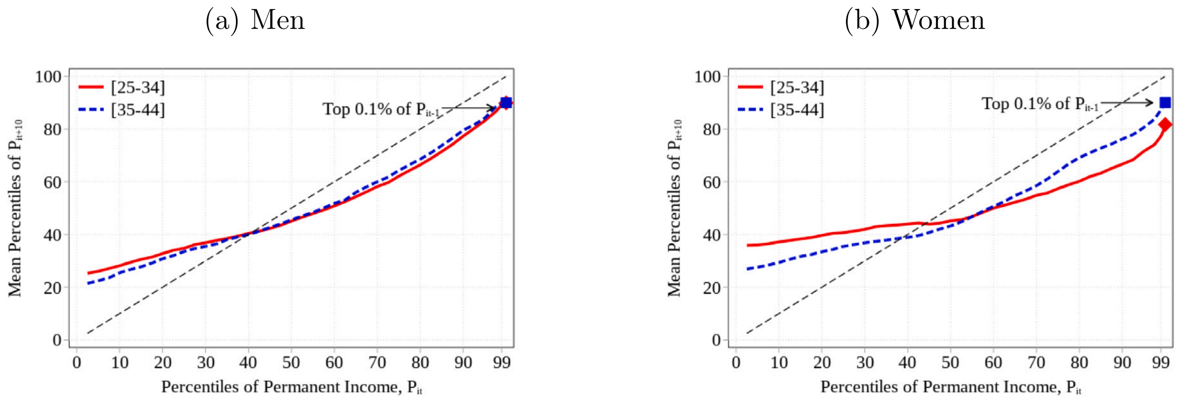

Fig. 10. 10-year earnings mobility by age.
Notes. This figure illustrates average rank-rank mobility by age and gender, plotting the permanent income percentile in year t against the mean permanent income percentile 10 years later. The dashed black line represents zero mobility, where individuals remain at the same percentile after 10 years.

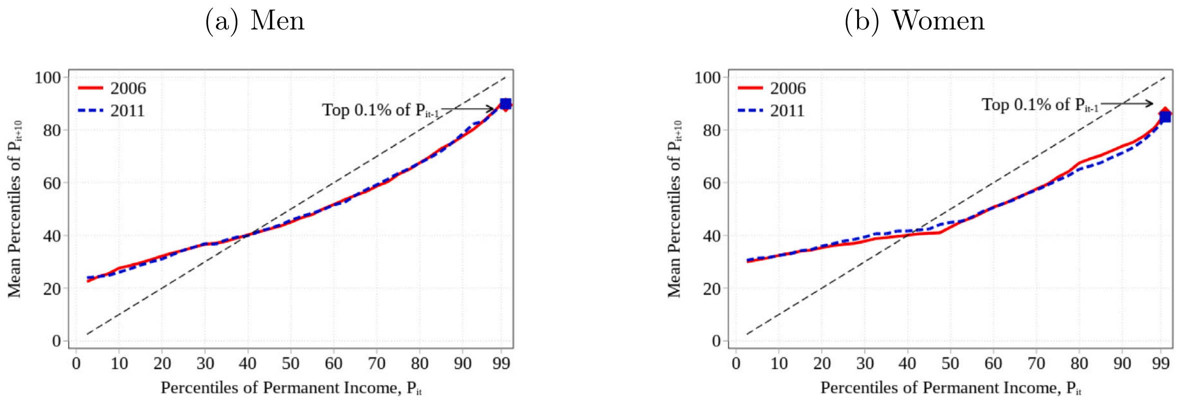

Fig. 11. 10-year earnings mobility by years.
Notes. This figure illustrates average rank-rank mobility across different points in time by gender, plotting the permanent income percentile in year t against the mean permanent income percentile 10 years later. The dashed black line represents perfect immobility, where individuals remain at the same percentile after 10 years.

4. Differing trends in earnings and wage dispersion

Section 3.2.1 documented a relatively stable path of annual earnings inequality, while Section 3.2.2 showed that hourly wage dispersion declined markedly over the same period. These two facts do not necessarily contradict each other. Annual earnings depend not only on wage rates, but also on how much people work — both in terms of hours worked and the number of days or months worked during the year. This section, therefore, decomposes earnings dispersion into wage and labor-supply components, asking which margins offset the compression in hourly wages.

We begin by linking annual earnings (E) to average monthly wage earnings (W). Let D denote the total number of days worked within a year. Then, annual earnings can be written as $E = W \times D$, which implies the following variance decomposition in logs:

$$\mathrm{Var}(\ln E) = \mathrm{Var}(\ln D) + 2\mathrm{Cov}(\ln D, \ln W) + \mathrm{Var}(\ln W) \tag{1}$$

This expression shows that the cross-sectional dispersion in annual earnings comprises three components: variation in average monthly earnings, variation in days worked over the year, and the covariance between them. The covariance term is expected to be positive if low earners experience more fragmented employment histories and spend fewer months in employment.

To further break down monthly earnings, we use information on average contracted weekly hours (H) and define average hourly wages as $w = W/H$. This yields a second decomposition:

$$\mathrm{Var}(\ln W) = \mathrm{Var}(\ln H) + 2\mathrm{Cov}(\ln H, \ln w) + \mathrm{Var}(\ln w) \tag{2}$$

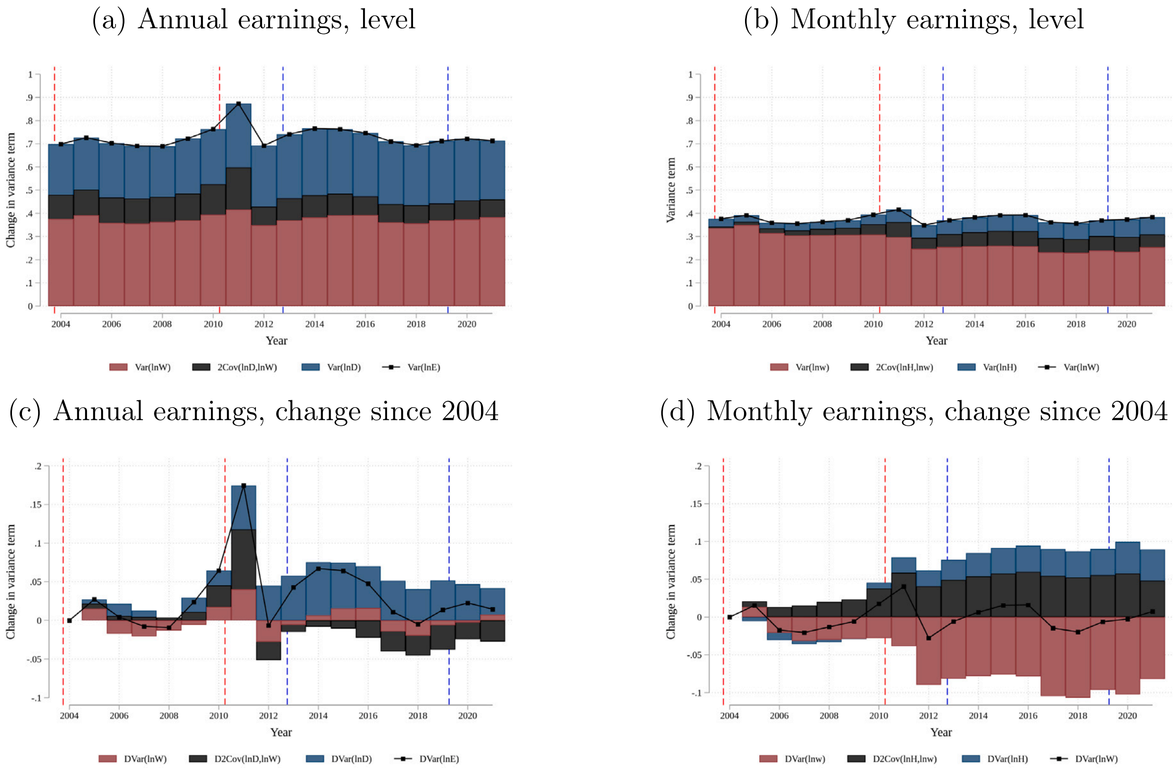

Fig. 12. Decomposition of annual and monthly earnings.
Notes. Panels (a) and (b) show the level of the variance decomposition of log annual earnings and log monthly earnings, respectively; panels (c) and (d) show the corresponding changes relative to 2004. For annual earnings, the decomposition is based on monthly earnings and months worked during the year; for monthly earnings, it is based on hourly wages and contracted weekly hours. The solid line indicates total variance, while the shaded areas show the contribution of the individual variance and covariance components. Vertical dashed lines mark the start and end years of the two subsample periods used in the later wage decomposition analysis: 2004–2010 and 2013–2019. The analysis is restricted to observations with non-missing contracted working hours.

Thus, dispersion in monthly earnings is driven by variation in hourly wages, variation in working hours, and their covariance. The covariance term is positive if working part-time is more common among low-wage workers.[10]

The two decompositions above hold not only for the variances and covariances at each year, but also for changes in these components between our first observed year (2004) and the given year. Fig. 12 presents the components of the two decompositions, both in levels and as changes since 2004.[11]

Panels (a) and (c) show that the variance of annual earnings remains relatively stable over time, with only modest fluctuations, apart from the pronounced temporary fluctuations around 2011–2012—likely reflecting a combination of the Great Recession and administrative changes in the data (see Section 2.2). Setting these years, as well as the COVID-affected years aside, we can distinguish between two broader periods, 2004–2010 and 2013–2019, of which the second has a somewhat higher level of annual earnings dispersion on average, as highlighted in panel (c). This higher dispersion is coming from an increased relevance of variation in months worked. In the second half of the 2010s, however, this dispersion is being offset by a slightly lower level of variation in monthly earnings and a decrease in the covariance term.[12]

Panels (b) and (d) present the corresponding decomposition for monthly earnings and reveal a markedly different pattern in terms of composition. While the overall dispersion of average monthly earnings is more stable than that of annual earnings, this stability masks important offsetting forces. In particular, the dispersion of hourly wages declines substantially over time. This pattern is especially pronounced from the mid-2000s onwards. The introduction of the skilled minimum wage in 2006, followed by large increases in both minimum wage tiers in 2012 and 2017 (see Section 2.1), coincided with clear compressions in the distribution of

[10] Or if working extra hours is more common among high-wage workers. Although it is possible that high-wage workers work more overtime, we can only observe contracted hours, which rarely exceed the usual 40 h per week.

[11] As this analysis relies on reported contracted working hours, we exclude spells with employment forms for which information on working hours is not available.

[12] Hoffmann et al. (2022), who report a similar decomposition for Italy, find a relatively stronger (and stable) role for the covariance term.

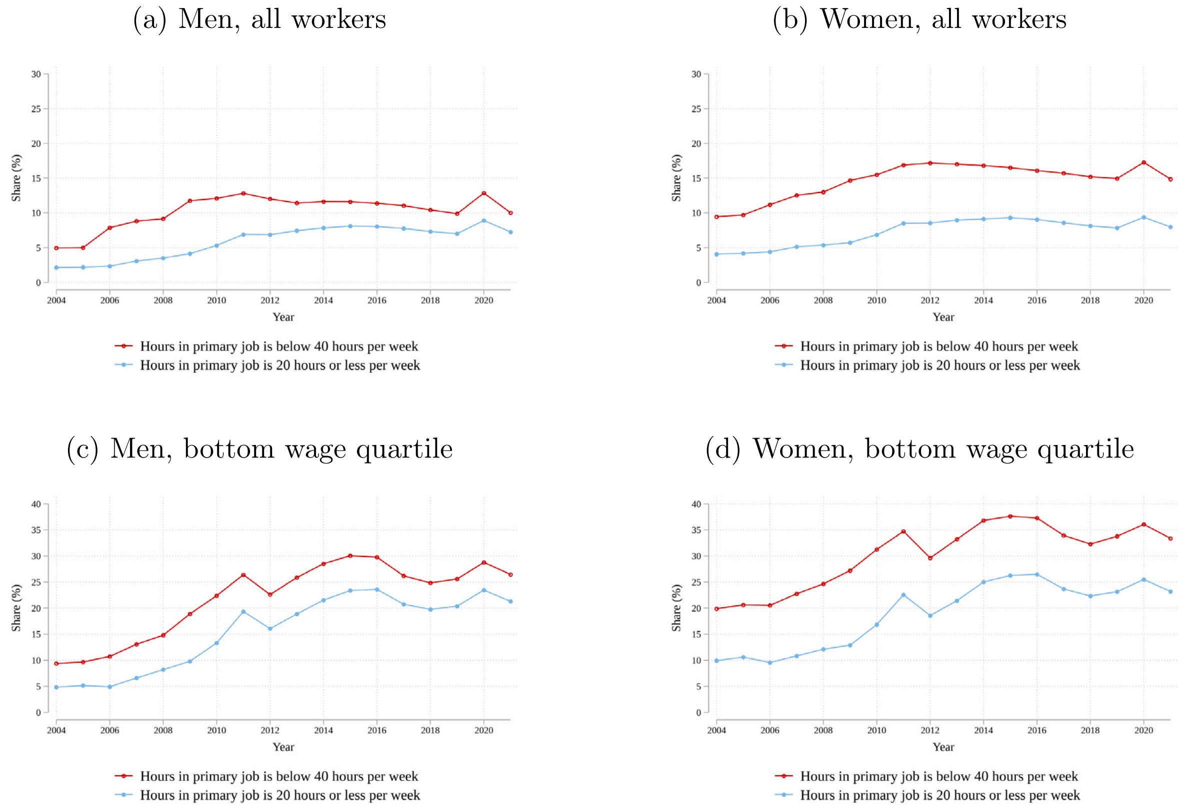

Fig. 13. Share of part-time workers.
Notes. This figure shows the share of workers with part-time contracts under two definitions based on weekly contracted working hours: less than 40 h per week, and 20 h or less per week. Panels (a) and (b) report these shares for all male and female employees, respectively, in the monthly sample with available information on contracted working hours. Panels (c) and (d) report the corresponding shares for workers in the bottom quartile of the hourly wage distribution, separately by gender. The bottom wage quartile is defined within years of the monthly wage sample.

hourly wages. However, these equalizing effects were offset by a gradual increase in the dispersion of working hours. At the same time, the covariance between hourly wages and hours worked becomes increasingly positive, indicating that reductions in working time are disproportionately concentrated among lower-wage workers.

The increase in hours dispersion is mainly driven by the expansion of part-time employment. In Fig. 13, we illustrate two different definitions for part-time work. While full-time work is most often considered as 40 h per week, and part-time as 20 h per week, 30 or 36 h arrangements are not uncommon either.

Panels (a) and (b) show that the overall share of part-time work rises steadily over the period for both men and women. While for the former, working part-time was relatively rare in the early 2000s, its incidence had doubled by 2020. For women, starting from a higher level, around a 50% increase was also present. The first waves of the COVID pandemic have temporarily increased the share of part-time work arrangements in 2020 for both genders.

Among low-wage workers, the incidence of part-time employment increases even more sharply from the mid-2000s onwards, as shown by panels (c) and (d). This pattern is consistent with the strong increase in the covariance term from the decomposition results and suggests that changes in working time are concentrated among workers close to the minimum wage.

Taken together, these results suggest that the flat trajectory of both annual and monthly earnings inequality reflects the interaction of two opposing forces: declining dispersion in hourly wages, consistent with rising wage floors, and increasing heterogeneity in labor supply along the intensive margin, especially among low earners.

This latter finding points to an important adjustment margin on the employer side. However, the administrative data do not allow us to distinguish fully between real reductions in working hours and changes in reporting practices. In particular, part of the increase in part-time employment may reflect the use of informal compensation schemes (so-called "envelope pay", for more details see Section 2.1), whereby workers are officially reported as working fewer hours while receiving additional undeclared income. Although survey-based evidence suggests that the prevalence of such practices declined during the 2010s, as Bíró et al. (2021) pointed out, increases in the minimum wage may not only raise formal labor costs but also influence firms' incentives to engage in informal wage arrangements. It is possible that while informal practices have decreased in the overall economy, these practices have gained extra momentum in the sub-population of earners around the minimum wage.

The decompositions in this section show that stable earnings inequality is not inconsistent with strong compression in hourly wages. Labor-supply margins, especially contracted hours among low-wage workers, offset part of the equalizing force coming from wage rates. The next question is therefore narrower: conditional on focusing only on hourly wages, which part of the wage structure compressed? In the next section, we leave aside annual earnings and labor-supply variation and use linked employer–employee methods to decompose hourly wages into worker, firm, and occupation components, together with the sorting terms that link them.

5. Firms, occupations, and wage sorting

Sections 3 and 4 showed that aggregate annual earnings inequality changed only modestly, while hourly wage dispersion compressed substantially. Section 4 attributed this divergence to offsetting labor-supply margins: hourly wages became more equal, but variation in contracted hours and employment intensity became more important. We now focus only on hourly wages and ask which parts of the wage structure were compressed. Wage compression may reflect narrower persistent differences between workers, weaker employer-specific wage premia, narrower occupational premia, or changes in the sorting of workers across firms and occupations.

To examine these margins, we estimate an AKM-style linked employer–employee model, extended with occupation effects, over two seven-year windows: 2004–2010 and 2013–2019. Worker effects capture persistent individual wage components after conditioning on employer and occupation. Firm effects capture employer-specific wage premia after accounting for worker and occupational composition. Occupation effects capture stable wage differences associated with tasks, credentials, and occupational wage premia.

The decomposition separates two types of changes. The variance terms show whether wage compression is associated with narrower dispersion in worker, firm, or occupation components. The covariance terms capture sorting: for example, whether high-wage workers are disproportionately employed by high-premium employers or concentrated in high-premium occupations. This distinction is important in the Hungarian setting because a rising wage floor may compress firm and occupation premia while leaving the allocation of workers across firms and occupations largely intact.

A large international literature shows that employer heterogeneity is an important component of wage inequality. In the original AKM framework, Abowd et al. (1999) show that persistent worker effects explain a large share of wage variation, while firm effects and the allocation of workers across firms also matter. For West Germany, Card et al. (2013) find that rising establishment wage premia and stronger assortative matching between workers and establishments account for a large part of the increase in wage inequality between the mid-1980s and the late 2000s. Related evidence for Portugal in Card et al. (2018) also points to a sizeable role of firm-specific pay premia and rent sharing. For the United States, Song et al. (2019) and Barth et al. (2016) show that much of the rise in earnings inequality occurred between firms or establishments rather than only within them, a pattern that Tomaskovic-Devey et al. (2020) also documents across a large set of countries. Evidence from Brazil provides a useful contrast: Alvarez et al. (2018) find that declining firm effects variation contributed substantially to the fall in earnings inequality. Unlike in most settings studied in the literature, hourly wage dispersion declined in Hungary over time. This allows us to examine whether the compression of wages was accompanied by lower dispersion in firm premia, occupational premia or worker heterogeneity.

To assess the structure of wage heterogeneity in Hungary, we estimate models that follow the seminal linked employer–employee framework of Abowd et al. (1999). In particular, we apply a log-additive wage specification, extended with occupation effects in the spirit of Torres et al. (2018). The model is defined as a regression of the log wages of individual i, working at firm j, in occupation k, at time t on some time-varying controls and the full set of time-invariant person, employer, and occupation fixed effects:

$$\ln\, w_{ijt} = \boldsymbol{X}_{ijt}\boldsymbol{\beta} + \theta_i + \psi_j + \lambda_k + \varepsilon_{ijt} \tag{3}$$

Here, ψ_j denotes the firm-specific wage premium of firm j, reflecting how much the given firm systematically pays above or below the market conditional on worker and job characteristics. The individual-specific term θ_i captures the persistent earning capacity independent of the current employer or occupation for worker i, including both observed and unobserved skills. The λ_k parameter represents the relative occupational wage ranking of occupation k.[13] Finally, $\boldsymbol{X}_{ijt}\boldsymbol{\beta}$ includes time-varying worker and job covariates such as age, tenure, and calendar year.[14]

Over the past two decades, the AKM model has served as a foundation for multiple approaches to decomposing wage dispersion. The *total variance decomposition* proposed by Abowd et al. (1999) and later by Card et al. (2013) can be expressed in our setting as

$$\begin{aligned} \mathrm{Var}(\ln\, w_{ijt}) = {} & \mathrm{Var}(\hat{\theta}_i) + \mathrm{Var}(\hat{\psi}_j) + \mathrm{Var}(\hat{\lambda}_k) + \mathrm{Var}(\boldsymbol{X}_{ijt}\hat{\boldsymbol{\beta}}) + \mathrm{Var}(\hat{\varepsilon}_{ijt}) \\ & + 2\mathrm{Cov}(\hat{\theta}_i, \hat{\psi}_j) + 2\mathrm{Cov}(\hat{\psi}_j, \hat{\lambda}_k) + 2\mathrm{Cov}(\hat{\theta}_i, \hat{\lambda}_k) \\ & + 2\mathrm{Cov}(\hat{\theta}_i, \boldsymbol{X}_{ijt}\hat{\boldsymbol{\beta}}) + 2\mathrm{Cov}(\hat{\psi}_j, \boldsymbol{X}_{ijt}\hat{\boldsymbol{\beta}}) + 2\mathrm{Cov}(\hat{\lambda}_k, \boldsymbol{X}_{ijt}\hat{\boldsymbol{\beta}}) \end{aligned} \tag{4}$$

[13] Torres et al. (2018) notes that even highly detailed occupational codes may not fully reflect differences in pay standards across sectors. For instance, a secretary in an IT firm may face different pay norms than a secretary in an assembly plant. Because sectoral collective agreements are relatively rare in Hungary, we use standardized occupation codes harmonized across the observation period. The connected set on which person, firm, and occupation effects are jointly identified is more restricted than in the two-way fixed effect case and is defined using the algorithm of Weeks and Williams (1964), as discussed by Cardoso et al. (2016), Torres et al. (2018), and Boza (2022).

[14] Real wages increased steadily during the 2010s. To prevent this trend from affecting the variance measures based on pooled data from multiple years, we remove the estimated year effects from wages.

Table 2
Variance decompositions of log wages over two periods.

	2004–2010	2013–2019	Change
Variance of log wages	0.324	0.267	−0.057
Ensemble decomposition (Card et al., 2018)			
Contribution of covariate index (XB)	1.2%	5.8%	4.7%
Contribution of individual heterogeneity (θ_i)	50.1%	51.5%	1.4%
Contribution of firm heterogeneity (ψ_j)	29.9%	23.1%	−6.8%
Contribution of occupational heterogeneity (λ_k)	12.2%	8.0%	−4.2%
Residual variation (ε_{ijt})	6.6%	11.6%	5.0%
Total variance decomposition (Card et al., 2013)			
Contribution of worker fixed effects	37.3%	39.2%	1.8%
Contribution of firm fixed effects	23.6%	17.2%	−6.4%
Contribution of occupation fixed effects	5.8%	2.6%	−3.2%
Contribution of worker–firm correlation	12.3%	12.1%	−0.2%
Contribution of worker–occupation correlation	12.7%	10.0%	−2.7%
Contribution of firm–occupation correlation	−0.3%	−0.5%	−0.2%
Contributions related to controls (XB)	1.8%	7.8%	5.9%
Residual variation	6.6%	11.6%	5.0%
Correlation of person and firm fixed effects	0.207	0.233	0.026
Number of:			
Observations (1000)	75 181	74 050	
Individuals (1000)	1608	1550	
Firms (1000)	86	91	
Occupations	333	333	
Share in largest connected set	85.1%	85.7%	

Notes. The table decomposes the variance of log hourly wages in two seven-year periods using the monthly wage sample. The ensemble decomposition follows Card et al. (2018); the total variance decomposition follows Card et al. (2013). Reported contributions are shares of total wage variance, except for the variance of log wages and the correlation of person and firm fixed effects. The change column reports the difference between 2013–2019 and 2004–2010. Observation, individual, and firm counts are in thousands.

This decomposition partitions overall wage variation into the variance of time-invariant worker-, firm-, and occupation-specific wage components, the covariate index, and the residual, plus all pairwise covariances among them. The covariance between worker and firm effects is particularly informative: it measures the presence of assortative matching in wages. Specifically, it captures the extent to which higher-wage workers are systematically more likely to be employed by higher-paying firms. With occupation effects included, the total variance decomposition also captures sorting between high-productivity firms and specific occupations, and the non-random selection of individuals into occupations. As emphasized by Torres et al. (2018), if well-paying jobs are concentrated within well-paying firms, omitting occupational heterogeneity may overstate the role of firm effects.

An alternative perspective is provided by the *ensemble decomposition* of Card et al. (2018), which rewrites the variance of wages as the sum of covariances between wages and each estimated component:

$$\mathrm{Var}(w_{ijt}) = \mathrm{Cov}(w_{ijt}, \boldsymbol{X}_{ijt}\hat{\boldsymbol{\beta}}) + \mathrm{Cov}(w_{ijt}, \hat{\theta}_i) + \mathrm{Cov}(w_{ijt}, \hat{\psi}_j) + \mathrm{Cov}(w_{ijt}, \hat{\lambda}_k) + \mathrm{Cov}(w_{ijt}, \hat{\varepsilon}_{ijt}) \tag{5}$$

Each covariance term quantifies how strongly wages co-vary with the corresponding component. A large covariance with individual fixed effects indicates that persistent worker heterogeneity explains a substantial part of wage dispersion, while strong covariance with firm effects implies that firm-specific pay premia are an important driver of differences across workers. In this accounting, interaction terms such as $2\mathrm{Cov}(\hat{\theta}_i, \hat{\psi}_j)$ are split equally between the contributing components.

Table 2 traces the evolution of wage dispersion and its building blocks across two multi-year periods, 2004–2010 and 2013–2019. Starting with the broadest fact, overall inequality in hourly pay has declined over time. This is visible in the variance of log wages, which falls from 0.324 in the earlier period to 0.267 in the later one, a drop of 0.057 points. One important factor behind this trend is the increase in minimum wages that compressed the wage distribution. The key question for the rest of the section is how this compression appears in the wage structure: whether it is reflected mainly in reduced dispersion of worker effects, narrower firm premia, narrower occupational premia, or changes in the sorting of workers across firms and occupations.

The ensemble decomposition helps unpack this by showing how the relative weight of different sources of wage variation shifts between the two periods. One small but clear change is that observed covariates (age, education, and experience) explain a somewhat larger share of wage dispersion in the second period. Their contribution rose from 1.2% in 2004–2010 to 5.8% in 2013–2019.

The largest shifts, however, are in the fixed-effect components. The worker component remains remarkably stable. It explains about half of the total wage variance in both periods: its share moves only from 50.1% to 51.5%. In other words, persistent worker heterogeneity (time-invariant differences in earning capacity across individuals) continues to be the single most important contributor to inequality without being able to explain the overall compression. By contrast, the firm and occupation components both contract noticeably. The firm share falls from 29.9% to 23.1%, and the occupation share from 12.2% to 8.0%. Put differently, there is less dispersion in wage premia across firms and across occupations in the later period than in the earlier one. This implies that "where you work" and "what you do" matter somewhat less for wage inequality than they used to, even though worker differences remain just as important.

Finally, the residual share rises from 6.6% to 11.6%. This means that a larger part of wage variation is left unexplained by observed covariates and by the persistent worker, firm, and occupation effects. This may reflect more short-term or idiosyncratic pay variation.

These patterns are consistent with the interpretation that rising minimum wages contributed to the observed compression in hourly wage inequality. In this reading, higher wage floors would compress pay differences across low-wage jobs and employers, thereby reducing the dispersion of firm- and occupation-specific premia. The results, therefore, point to a change in the wage structure across firms and occupations, rather than to a decline in persistent differences between workers.[15]

In the total variance decomposition, the worker–firm correlation term remains large, contributing 12.3% of wage variance in 2004–2010 and 12.1% in 2013–2019. Thus, while firm premia themselves decline, the association between high-wage workers and high-paying employers remains an important component of wage dispersion. The simple correlation between person and firm fixed effects also remains positive, increasing from 0.207 to 0.233. Worker–occupation sorting declines from 12.7% to 10.0%, while the firm–occupation correlation is close to zero in both periods. This suggests that, in our setting, the firm–occupation channel emphasized by Torres et al. (2018) is limited: high-premium firms do not appear to be systematically concentrated in high-premium occupations once worker and occupation effects are separately estimated.

Putting the ensemble and total variance decompositions together, three results stand out. First, persistent worker heterogeneity remains the largest component of wage dispersion. In the ensemble decomposition, individual heterogeneity accounts for about half of the total wage variance in both periods. Second, firm and occupation premia both decline: the ensemble contribution of firm heterogeneity falls from 29.9% to 23.1%, and that of occupational heterogeneity from 12.2% to 8.0%. The total variance decomposition points in the same direction, with the firm fixed-effect contribution falling from 23.6% to 17.2% and the occupation fixed-effect contribution from 5.8% to 2.6%. Third, worker–firm sorting remains important but does not increase in the baseline specification: its contribution is 12.3% in the first period and 12.1% in the second. Overall, the compression of hourly wage dispersion appears to come mainly from declining variation in firm and occupation premia rather than from changes in persistent worker heterogeneity.

These results contrast with AKM-based evidence from countries where wage inequality increased. For West Germany, Card et al. (2013) find that rising establishment premia and stronger assortative matching contributed substantially to growing wage inequality. Related evidence for the United States and a broader set of countries highlights the increasing importance of between-firm or between-establishment differences in earnings inequality (Barth et al., 2016; Song et al., 2019; Tomaskovic-Devey et al., 2020). Hungary instead shows declining firm and occupation premia, with stable worker heterogeneity and persistent worker–firm sorting. This makes the Hungarian pattern closer to cases of wage compression, such as Brazil in Alvarez et al. (2018), although the likely institutional channel differs.

As in most AKM applications, identification and precision are sensitive to limited worker mobility between firms (Andrews et al., 2012). Such limited mobility can bias the variance of estimated firm effects (as they are measured with less precision) and their covariances. While a full set of bias-correction exercises is beyond the scope of this chapter, we complement the main results with a simple correction exercise based on the clustering approach of Bonhomme et al. (2019), replacing almost 100,000 individual firm effects with 100 firm-cluster effects constructed from firms with similar internal wage structures.[16]

Table A.2 contains the results obtained by this approach.[17] Similarly to examples in the recent literature, we find that the correlation between the firm and person effects and the corresponding estimated contribution to overall wage dispersion became substantially larger, while the direct contribution of firms in themselves, as indicated by $Var(\psi_j)$ in the second panel, decreased somewhat. The magnitude of the former increase is especially large as the worker–firm sorting component is now estimated to be 20.9% and 22.3% in the two periods, almost twice the size of the baseline estimations in Table 2. This further emphasizes the importance of sorting in Hungary: even as minimum-wage increases raise wage levels in lower-paying firms, high-wage workers continue to be disproportionately employed by high-premium employers.

6. Conclusion

Our analysis of earnings inequality, volatility, and mobility in Hungary between 2004 and 2021 reveals a labor market characterized by modest aggregate changes in earnings inequality but substantial heterogeneity underneath the surface. Aggregate earnings dispersion remained broadly stable, with slight increases in top-end inequality among men and rising lower-tail inequality among young workers. Earnings dynamics are also strongly gendered: men experience relatively stable and symmetric earnings fluctuations, whereas women, especially at prime working ages, face higher volatility, skewness, and kurtosis, consistent with career interruptions and labor-supply changes around family formation.

[15] The increase in residual variation is also consistent with this interpretation. If wage floors bind more often in the later period, some low-wage workers in low-premium firms or occupations may earn more than predicted by their worker, firm, and occupation effects; this remaining spell-level variation would then enter the residual component.

[16] Also, while we do not include many robustness tests and specification tests, Boza (2022) provides such exercises for the same decompositions on an earlier, shorter version of the dataset.

[17] We note that the results relate to a somewhat larger set of observations, as with firm-clusters as units of aggregation, all observations become part of the largest connected set on which the firm(-cluster) effects are identified, since none of the firm clusters is disjoint from the rest of the economy.

A central finding is that stable earnings dispersion masks offsetting movements in wage rates and labor supply. Hourly wage dispersion declined markedly, especially around periods of large minimum-wage increases, but this compression did not translate into a comparable decline in monthly or annual earnings dispersion. The decomposition of earnings into wage and labor-supply components highlights the underlying mechanisms: variation in contracted hours and employment intensity became more important, especially among low-wage workers. Thus, earnings inequality in Hungary cannot be understood from wage rates alone. The labor-supply margins, and possibly reporting practices around part-time work and undeclared pay, are central to the link between wage compression and observed earnings inequality.

The AKM-based total variance and ensemble decompositions clarifies where the compression of hourly wages appears in the wage structure. Persistent worker heterogeneity remains the dominant component of wage dispersion, accounting for roughly half of total variance in both periods. By contrast, firm and occupation premia decline, suggesting that employer- and occupation-specific wage differences became less dispersed over time. This pattern is consistent with rising wage floors compressing pay differences across low-wage employers and occupations, rather than with a decline in persistent worker heterogeneity. At the same time, worker–firm sorting remains quantitatively important, and the bias-corrected specification points to a particularly strong role for assortative matching between high-wage workers and high-premium employers.

Taken together, the Hungarian evidence highlights a distinction between wage compression and earnings-equality gains. Strong wage growth and rising wage floors compressed parts of the hourly wage structure, but their equalizing force was partly offset by changes in hours and employment intensity. The Hungarian case therefore adds to the GRID evidence by showing how a relatively stable path of annual earnings inequality can coexist with substantial changes in wage-setting margins, labor supply, and worker–employer sorting. Future work could examine more directly whether the growth of part-time contracts around the bottom of the wage distribution reflects real hours adjustment, reporting responses, or broader changes in employer wage-setting practices.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

A.1. Additional tables and figures

See Tables A.1 and A.2 Figs. A.1–A.4

Table A.1
Employment types included in the analysis samples.

Employment category	Included in		Employment share in		
	ED	WD	A4	ED	WD
Employee under standard employment contract	Yes	Yes	70.1%	78.7%	82.9%
Civil servant, judge, prosecutor, politician, mayor	Yes	Yes	3.2%	3.6%	3.8%
Public employee	Yes	Yes	11.2%	12.6%	13.3%
Member of a lawful state coercive force/armed service	No[a]	No[a]	1.8%		
Member of a cooperative	No	No	0.1%		
Incorporated entrepreneur/ business partner in a company	No	No	3.0%		
Self-employed sole proprietor/individual entrepreneur	No	No	5.2%		
Outworker, assignment-based or contractor-type legal relationship, usage/licensing contract	Yes	No	0.5%	0.6%	
Agricultural primary producer	No	No	0.8%		
Casual worker/worker under simplified employment	Yes	No	1.8%	2.0%	
Other employment relationship	Yes	No	0.2%	0.2%	
Public works employee/ publicly employed worker	Yes	No	2.0%	2.2%	
Share in full dataset:			**100.0%**	**89.1%**	**84.6%**

Notes. Distribution of employment types over active person-months in the used datasets. A4: Admin4 (full) dataset, ED: Earnings Data, WD: Wage Data. For individuals with concurrent spells in any month, we use the primary one, which provides the most earnings in the given month.

[a] Although members of the armed forces have earnings, contracted hours, and wage data, their employment records were stored in a separate system before 2012. To keep the sample population consistent over time, we exclude these employment spells from the dataset throughout the full observation period.

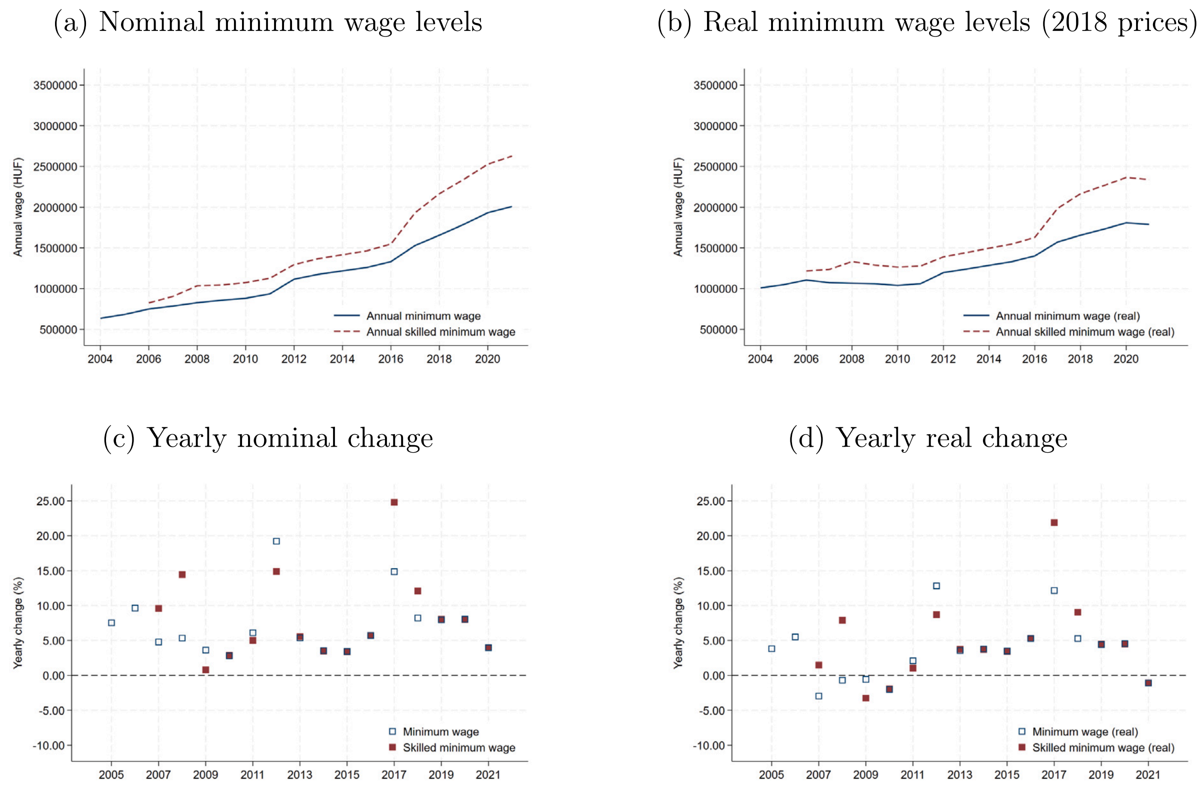

Fig. A.1. Minimum wages in Hungary, 2004–2021.
Notes. This figure shows the evolution of minimum wages in Hungary. Hungary has operated a differentiated minimum wage system since 2006: the minimum wage applies to all workers, while the skilled minimum wage (guaranteed wage minimum) applies to workers in jobs requiring at least secondary education or a vocational qualification. Panels (a) and (b) display the nominal and real annual minimum wage levels (the sum of monthly minimum wages over the twelve months of the given year), respectively, with real values deflated to 2018 prices. Panels (c) and (d) show the corresponding year-on-year percentage changes in nominal and real terms.

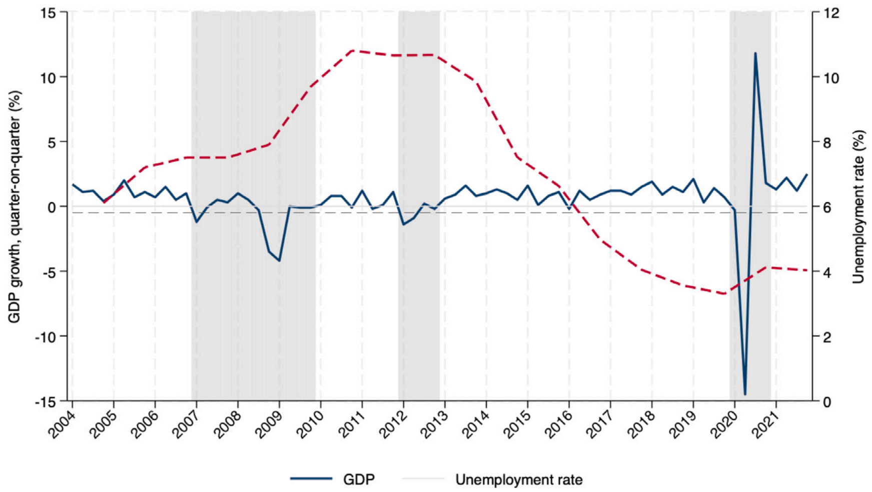

Fig. A.2. GDP and unemployment rate in Hungary.
Notes. This figure shows the quarterly percentage change in real GDP (left axis, quarter-on-quarter) and the annual unemployment rate (right axis) in Hungary over the period 2004–2021. GDP is measured as a seasonally and calendar-adjusted, balanced volume index (quarter-on-quarter). Shaded areas indicate recession years, defined as years in which GDP growth fell below −0.5% in at least one quarter. Prior to 2009, the unemployment rate covers the 15–64 age group, while from 2009 onward, the series is extended to the 15–74 age group, reflecting the adoption of the revised ILO/Eurostat definition.
Source: Hungarian Statistical Office (KSH, Tables 21.2.1.2. (GDP) and 20.2.1.2., and 2.3.2. (Unemployment)).

Table A.2
Variance decompositions of log wages — firm-cluster approach.

	2004–2010	2013–2019	Change
Variance of log wages	0.330	0.275	−0.054
Ensemble decomposition (Card et al., 2018)			
Contribution of covariate index (XB)	1.1%	2.3%	1.2%
Contribution of individual heterogeneity (θ_i)	47.5%	49.6%	2.1%
Contribution of firm heterogeneity (ψ_j)	34.1%	30.2%	−3.9%
Contribution of occupational heterogeneity (λ_k)	9.2%	5.5%	−3.7%
Residual variation (ε_{ijt})	8.0%	12.4%	4.4%
Total variance decomposition (Card et al., 2013)			
Contribution of worker fixed effects	33.2%	35.6%	2.4%
Contribution of firm fixed effects	21.7%	17.3%	−4.4%
Contribution of occupation fixed effects	3.7%	1.5%	−2.3%
Contribution of worker–firm correlation	20.9%	22.3%	1.4%
Contribution of worker–occupation correlation	7.5%	5.7%	−1.8%
Contribution of firm–occupation correlation	3.3%	2.2%	−1.2%
Contributions related to controls (XB)	1.7%	3.1%	1.4%
Residual variation	8.0%	12.4%	4.4%
Correlation of person and firm fixed effects	0.389	0.449	0.059
Number of:			
Observations (1000)	88 100	84 852	
Individuals (1000)	1842	1750	
Firm clusters	100	100	
Occupations	333	333	
Share in largest connected set	85.1%	85.7%	

Notes. The table decomposes the variance of log hourly wages in two seven-year periods using the monthly wage sample. The ensemble decomposition follows Card et al. (2018); the total variance decomposition follows Card et al. (2013). Reported contributions are shares of total wage variance, except for the variance of log wages and the correlation of person and firm fixed effects. The change column reports the difference between 2013–2019 and 2004–2010. Observation and individual counts are in thousands. Bias-corrected results replace individual firm effects with 100 firm-cluster effects, following the grouped fixed-effect approach of Bonhomme et al. (2019). Clusters are constructed using K-means based on 21 percentiles of each firm's wage distribution: the 1st, every 5th percentile from 5 to 95, and the 99th percentile. The clusters therefore group firms with similar internal wage distributions, reducing limited-mobility bias at the cost of a less flexible firm-effect structure. Fig. A.4 shows the resulting clusters ranked by median wages. Results are similar when using 500 clusters.

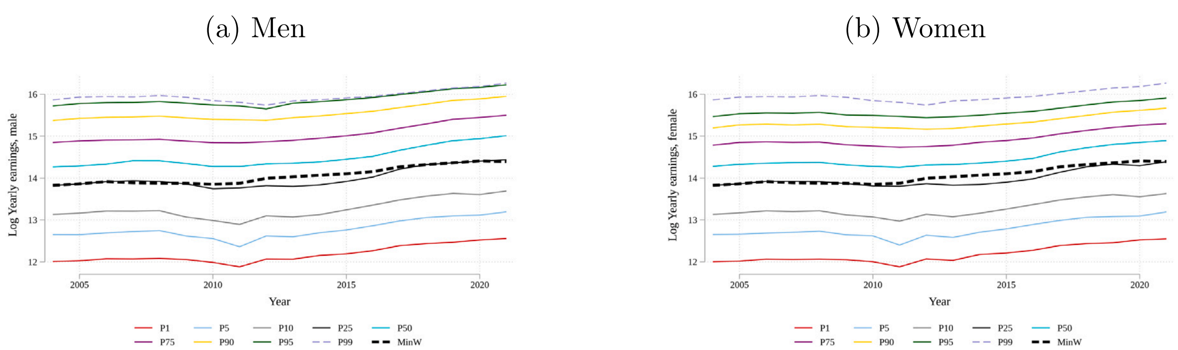

Fig. A.3. Earnings percentiles and the annualized minimum wage, 2004–2021.
Notes. This figure shows selected percentiles of the distribution of log real annual earnings together with the annualized statutory minimum wage, separately by gender. All values are expressed in 2018 prices. P99 values are affected by the winsorization applied to the data.

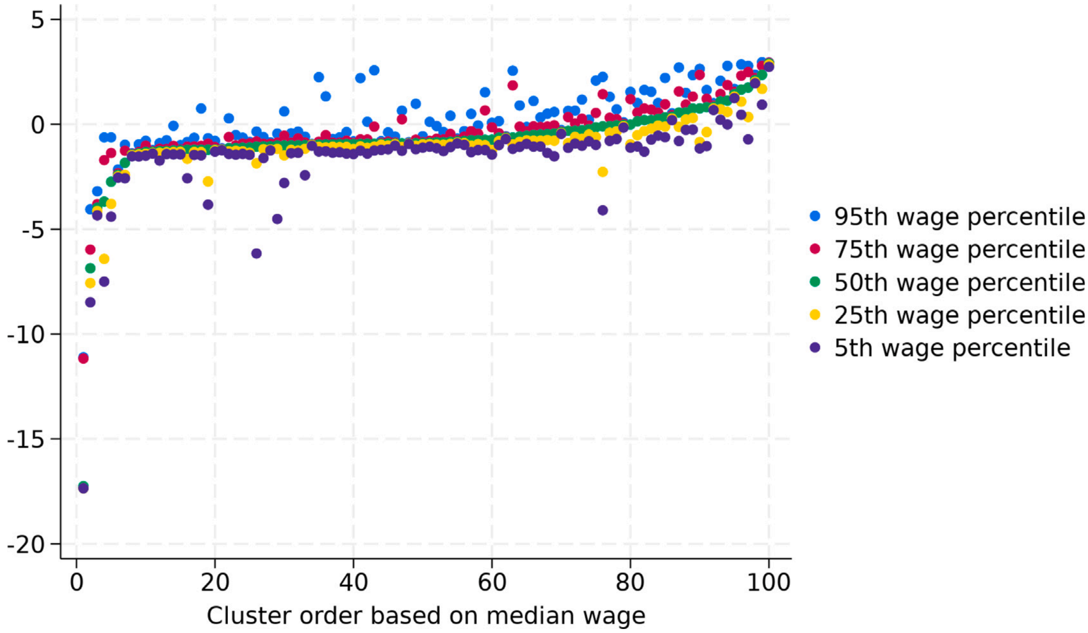

Fig. A.4. Wage percentiles of the clusters used in the bias-correction method.
Notes. This figure shows selected wage percentiles for the 100 firm clusters used in the bias-correction procedure. Clusters are ranked by their average median wage. For each cluster, the figure reports the distribution of log hourly wages, allowing comparison of both central tendency and within-cluster wage dispersion across the cluster ranking.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jmacro.2026.103779.

Data availability

The authors do not have permission to share data.

References

Abowd, J.M., Kramarz, F., Margolis, D.N., 1999. High wage workers and high wage firms. Econometrica 67 (2), 251–333. http://dx.doi.org/10.1111/1468-0262.00020, URL http://doi.wiley.com/10.1111/1468-0262.00020.

Alvarez, J., Benguria, F., Engbom, N., Moser, C., 2018. Firms and the decline in earnings inequality in Brazil. Am. Econ. J.: Macroecon. 10 (1), 149–189. http://dx.doi.org/10.1257/mac.20150355.

Andrews, M.J., Gill, L., Schank, T., Upward, R., 2012. High wage workers match with high wage firms: Clear evidence of the effects of limited mobility bias. Econom. Lett. 117 (3), 824–827. http://dx.doi.org/10.1016/j.econlet.2012.07.033, URL https://www.sciencedirect.com/science/article/pii/S0165176512004272.

Arellano, M., Bonhomme, S., De Vera, M., Hospido, L., Wei, S., 2022. Income risk inequality: Evidence from spanish administrative records. Quant. Econ. 13 (4), 1747–1801. http://dx.doi.org/10.3982/QE1887, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.3982/QE1887, URL https://onlinelibrary.wiley.com/doi/abs/10.3982/QE1887.

Barth, E., Bryson, A., Davis, J.C., Freeman, R., 2016. It's where you work: Increases in earnings dispersion across establishments and individuals in the United States. J. Labor Econ. 34 (S2), S67–S97. http://dx.doi.org/10.1086/684045.

Bell, B., Bloom, N., Blundell, J., 2022. Income dynamics in the United Kingdom and the impact of the Covid-19 recession. Quant. Econ. 13 (4), 1849–1878. http://dx.doi.org/10.3982/QE1872, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.3982/QE1872, URL https://onlinelibrary.wiley.com/doi/abs/10.3982/QE1872.

Bíró, A., Prinz, D., Sándor, L., 2021. The Minimum Wage, Informal Pay and Tax Enforcement. IFS Working Paper No. W21/41, Institute for Fiscal Studies, London, http://dx.doi.org/10.1920/wp.ifs.2021.4121, URL https://real.mtak.hu/164367/1/WP202141-The-minimum-wage-informal-pay-and-tax-enforcement.pdf.

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

Bonhomme, S., Lamadon, T., Manresa, E., Kline, P., Hansen, C., Sølvsten, M., Altonji, J., Graham, B., Lise, J., Lopes De Melo, R., Meghir, C., Mogstad, M., Neal, D., Pistaferri, L., Robin, J.-M., Rosen, A., Saggio, R., Schoenberg, U., Shimer, R., 2019. A distributional framework for matched employer employee data. Econometrica 87 (3), 699–739. http://dx.doi.org/10.3982/ecta15722.

Bowlus, A., Gouin-Bonenfant, É., Liu, H., Lochner, L., Park, Y., 2022. Four decades of Canadian earnings inequality and dynamics across workers and firms. Quant. Econ. 13 (4), 1447–1491.

Boza, I., 2022. Wage Differentials and the Possibilities in Linked Employer-Employee Panel Data (Ph.D. thesis). Central European University, http://dx.doi.org/10.14754/CEU.2022.01.

Boza, I., Szabó-Morvai, Á., 2025. Gyermekvállalás és az anyák keresete a 2010-es években. Közgazdasági Szle. 72 (6), 566–595. http://dx.doi.org/10.18414/KSZ.2025.6.566.

Card, D., Cardoso, A.R., Heining, J., Kline, P., 2018. Firms and labor market inequality: Evidence and some theory. J. Labor Econ. 36 (S1), S13–S70. http://dx.doi.org/10.1086/694153, https://www.journals.uchicago.edu/doi/10.1086/694153 http://www.journals.uchicago.edu/t-and-c.

Card, D., Heining, J., Kline, P., 2013. Workplace heterogeneity and the rise of west german wage inequality. Q. J. Econ. 128 (3), 967–1015. http://dx.doi.org/10.1093/qje/qjt006, URL https://eml.berkeley.edu/{~}cle/e250a_f14/paper1.pdf.

Cardoso, A.R., Guimarães, P., Portugal, P., 2016. What drives the gender wage gap? A look at the role of firm and job-title heterogeneity. Oxf. Econ. Pap. 68 (2), 506–524. http://dx.doi.org/10.1093/oep/gpv069, https://academic.oup.com/oep/article-lookup/doi/10.1093/oep/gpv069 https://academic.oup.com/oep/article/68/2/506/2364425.

Cengiz, D., Dube, A., Lindner, A., Zipperer, B., 2019. The effect of minimum wages on low-wage jobs. Q. J. Econ. 134 (3), 1405–1454.

Drechsel-Grau, M., Peichl, A., Schmid, K.D., Schmieder, J.F., Walz, H., Wolter, S., 2022. Inequality and income dynamics in Germany. Quant. Econ. 13 (4), 1593–1635. http://dx.doi.org/10.3982/QE1912, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.3982/QE1912, URL https://onlinelibrary.wiley.com/doi/abs/10.3982/QE1912.

Dube, A., Lindner, A., 2024. Minimum wages in the 21st century. Handb. Labor Econ. 5, 261–383.

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

Engbom, N., Moser, C., 2022. Earnings inequality and the minimum wage: Evidence from Brazil. Am. Econ. Rev. 112 (12), 3803–3847.

Eurofound, 2007. Partial opening of labour market to workers from new member states. URL https://www.eurofound.europa.eu/en/publications/all/partial-opening-labour-market-workers-new-member-states, Eurofound article.

European Central Bank, 2016. Wage Dynamics Network (WDN) Country Report: Hungary. Technical Report, European Central Bank, URL https://www.ecb.europa.eu/home/pdf/research/wdn/country_reports/WDN-Country_Report-Hungary.pdf.

European Commission, 2011. Free movement: Workers from eight member states that joined EU in 2004 finally enjoy full rights. URL https://ec.europa.eu/commission/presscorner/detail/en/ip_11_506, Press release IP/11/506.

European Commission, 2020. Special Eurobarometer 498: Undeclared Work in the European Union. Tech. Rep., European Commission, Brussels, http://dx.doi.org/10.2760/494496, URL https://europa.eu/eurobarometer/surveys/detail/2250, Wave EB92.1; fieldwork September 2019; conducted by Kantar Public.

European Labour Authority, 2023. Factsheet on Undeclared Work – Hungary. Tech. Rep., European Labour Authority, Bratislava, URL https://www.ela.europa.eu/sites/default/files/2024-02/FR-UDW_factsheet-2023-fin_0.pdf, Manuscript completed in March 2023.

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

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

Halvorsen, E., Ozkan, S., Salgado, S., 2022. Earnings dynamics and its intergenerational transmission: Evidence from Norway. Quant. Econ. 13 (4), 1707–1746. http://dx.doi.org/10.3982/QE1849, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.3982/QE1849, URL https://onlinelibrary.wiley.com/doi/abs/10.3982/QE1849.

Hoffmann, E.B., Malacrino, D., Pistaferri, L., 2022. Earnings dynamics and labor market reforms: The Italian case. Quant. Econ. 13 (4), 1637–1667. http://dx.doi.org/10.3982/QE1865, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.3982/QE1865, URL https://onlinelibrary.wiley.com/doi/abs/10.3982/QE1865.

Kátay, G., 2011. Downward Wage Rigidity in Hungary. ECB Working Paper No. 1372, European Central Bank (ECB), Frankfurt a. M., URL https://hdl.handle.net/10419/153806.

Kramarz, F., Nimier-David, E., Delemotte, T., 2022. Inequality and earnings dynamics in France: National policies and local consequences. Quant. Econ. 13 (4), 1527–1591.

Krekó, J., Erős, H., Greskovics, B., Hajnal, Á., Scharle, Á., 2023. The redistributive effect of the hungarian flat tax and family allowance system. Acta Oeconomica 73 (4), 481–503.

Lazzari, E., Compans, M.-C., Beaujouan, E., 2025. Change in the perceived reproductive age window and delayed fertility in Europe. Popul. Stud. 79 (1), 81–101. http://dx.doi.org/10.1080/00324728.2023.2298678.

Leth-Petersen, S., Sæverud, J., 2022. Inequality and dynamics of earnings and disposable income in Denmark 1987–2016. Quant. Econ. 13 (4), 1493–1526. http://dx.doi.org/10.3982/QE1843, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.3982/QE1843, URL https://onlinelibrary.wiley.com/doi/abs/10.3982/QE1843.

Lindner, A., Reizer, B., Weber, A., 2025. The Labor Market Effects of Worker Outflow: Evidence from Hungary. KRTK-KTI Working Papers No. 2025/14, HUN-REN Centre for Economic and Regional Studies, Institute of Economics, URL https://kti.krtk.hu/publikacio/the-labor-market-effects-of-worker-outflow-evidence-from-hungary/.

Magyar Nemzeti Bank, 2017. Labour Market and Wage Developments in Hungary. Tech. Rep. No. 135, Magyar Nemzeti Bank, URL https://www.mnb.hu/letoltes/mnb-op-135-final.pdf.

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

Puggioni, D., Calderón, M., Cebreros Zurita, A., Fernández Bujanda, L., Inguanzo González, J.A., Jaume, D., 2022. Inequality, income dynamics, and worker transitions: The case of Mexico. Quant. Econ. 13 (4), 1669–1705. http://dx.doi.org/10.3982/QE1863, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.3982/QE1863, URL https://onlinelibrary.wiley.com/doi/abs/10.3982/QE1863.

Song, J., Price, D.J., Guvenen, F., Bloom, N., Von Wachter, T., 2019. Firming up inequality. Q. J. Econ. 134 (1), 1–50. http://dx.doi.org/10.1093/qje/qjy025, https://academic.oup.com/qje/article/134/1/1/5144785 http://www.census.gov/econ/susb/historical.

Svraka, A., 2021. Recent Trends in Income Inequalities in Hungary Using Administrative Data. Taxation Working Papers No. 8, Ministry of Finance, Department of Tax Policy and International Taxation, URL https://ideas.repec.org/p/auo/moftwp/8.html.

Szabó, L.T., 2024. The effect of labour tightness on wages at the regional level in central Europe. J. Labour Mark. Res. 58 (15), http://dx.doi.org/10.1186/s12651-024-00383-w.

Telegdy, Á., 2018. Wage inequality on the hungarian labour market: Technological change, expansion in higher education and the role of the minimum wage. Financ. Econ. Rev. 17 (3), 5–28.

Tomaskovic-Devey, D., Rainey, A., Avent-Holt, D., Bandelj, N., Boza, I., Cort, D., Godechot, O., Hajdu, G., Hällsten, M., Henriksen, L.F., Hermansen, A.S., Hou, F., Jung, J., Kanjuo-Mrčela, A., King, J., Kodama, N., Kristal, T., Krízková, A., Lippényi, Z., Melzer, S.M., Mun, E., Penner, A., Petersen, T., Poje, A., Safi, M., Thaning, M., Tufail, Z., 2020. Rising between-workplace inequalities in high-income countries. Proc. Natl. Acad. Sci. USA 117 (17), 9277–9283. http://dx.doi.org/10.1073/pnas.1918249117, URL www.pnas.org/cgi/doi/10.1073/pnas.2009782117www.pnas.org.

Torres, S., Portugal, P., Addison, J.T., Guimarães, P., 2018. The sources of wage variation and the direction of assortative matching: Evidence from a three-way high-dimensional fixed effects regression model. Labour Econ. 54, 47–60. http://dx.doi.org/10.1016/j.labeco.2018.06.004, URL https://linkinghub.elsevier.com/retrieve/pii/S0927537117300489.

Weeks, D.L., Williams, D.R., 1964. A note on the determination of connectedness in an N-way cross classification. Technometrics 6 (3), 319–324. http://dx.doi.org/10.1080/00401706.1964.10490188.

World Inequality Database, 2026. Hungary. URL https://wid.world/country/hungary/, (Accessed 11 May 2026), Inequality Database country profile.