Labour market power and wage inequalities in European regions

Munkaerőpiaci hatalmi és bérkülönbségek az európai régiókban

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ABSTRACT: Despite a gradual decline in interpersonal wage inequality in many advanced economies, substantial spatial disparities in wages persist across European regions. This paper examines the extent to which employer wage-setting power (labour market power) contributes to these regional wage differences, with particular attention to its heterogeneous effects across the wage distribution and between metropolitan and non-metropolitan areas. While urban labour markets are generally associated with higher wages due to agglomeration economies and greater returns to skills, they may also amplify employer wage-setting power through stronger worker competition, weaker collective action, and greater employer discretion.

The paper makes two main contributions. Conceptually, it develops a framework linking labour market power to wage compression across the wage distribution, arguing that employer wage-setting power is likely to impose larger penalties on high-wage workers, particularly in metropolitan labour markets. Empirically, it provides new evidence on wage inequality across European Union NUTS 2 regions using the CompNet database. The analysis combines regional measures of wage dispersion with a comprehensive set of indicators capturing labour market imperfections, including labour markdowns, product market power, labour market concentration, and exposure to robotisation.

The results reveal persistent regional heterogeneity in wage levels and wage inequality despite Europe's comparatively moderate overall inequality. Labour markdowns are consistently associated with lower wages throughout the wage distribution, with the strongest effects at the upper percentiles, suggesting that employer wage-setting power compresses wages from above by disproportionately reducing the earnings of high-wage workers. These findings remain robust after accounting for alternative sources of market power and technological change.

The analysis further shows that these effects are significantly stronger in metropolitan regions. Labour markdowns exert a larger wage-depressing effect in urban labour markets, especially among high-skilled and high-paid workers, suggesting that cities intensify monopsonistic pressures through dense labour market competition and weaker worker bargaining power. These findings offer a novel perspective on the

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interaction between urbanisation and labour market power, highlighting the microeconomic mechanisms through which metropolitan labour markets shape wage outcomes.

Overall, the paper identifies labour market power as an important but often overlooked determinant of regional wage inequality in Europe. The results suggest that reducing territorial disparities requires not only redistributive policies but also stronger labour market institutions, including collective bargaining and enforcement mechanisms, alongside place-based policies that preserve the productivity advantages of cities while limiting excessive employer wage-setting power.

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KULCSSZAVAK: bérkülönbségek; munkaerő-piaci erő; árcsökkentés; nagyvárosi régiók

ABSZTRAKT: Annak ellenére, hogy számos fejlett gazdaságban fokozatosan csökken az egyének közötti bérkülönbség, az európai régiók között továbbra is jelentős térbeli bérkülönbségek tapasztalhatók. Ez a tanulmány azt vizsgálja, hogy a munkáltatók bérmegállapítási ereje (munkaerő-piaci hatalom) milyen mértékben járul hozzá ezekhez a regionális bérkülönbségekhez, különös figyelmet fordítva annak heterogén hatásaira a béreloszláson belül, valamint a nagyvárosi és nem nagyvárosi területek között. Bár a városi munkaerőpiacok általában magasabb bérekkel járnak együtt az agglomerációs megtakarítások és a képzettségből származó nagyobb hozamok miatt, ugyanakkor a munkavállalók közötti erősebb verseny, a gyengébb kollektív fellépés és a munkáltatók nagyobb mérlegelési jogköre révén felerősíthetik a munkáltatók bérmegállapítási erejét is.

A tanulmány két fő szempontból járul hozzá a témához. Elméleti szempontból olyan keretrendszert dolgoz ki, amely összekapcsolja a munkaerő-piaci hatalmat a béreloszláson belüli bérkompresszióval, és azzal érvel, hogy a munkáltatók bérmegállapítási ereje valószínűleg nagyobb hátrányokat ró a magas bérű munkavállalókra, különösen a nagyvárosi munkaerőpiacokon. Empirikusan új bizonyítékokat szolgáltat az Európai Unió NUTS 2 régiói közötti bérkülönbségekről a CompNet adatbázis felhasználásával. Az elemzés ötvözi a bérszóródás regionális mutatóit a munkaerőpiac tökéletlenségeit leképező átfogó mutatókészlettel, beleértve a bércsökkentéseket, a termékpiaci erőfölényt, a munkaerőpiaci koncentrációt és a robotizációval szembeni kitettséget.

Az eredmények azt mutatják, hogy a bérek szintje és az egyenlőtlenség terén tartós regionális heterogenitás figyelhető meg, annak ellenére, hogy Európában az általános egyenlőtlenség viszonylag mérsékelt. A munkaerő-leértékelés következetesen alacsonyabb bérekkel jár a béreloszlás egészében, a legerőteljesebb hatások pedig a felső percentilisekben jelentkeznek, ami arra utal, hogy a munkáltatók bérmegállapítási ereje felülről nyomja le a béreket azáltal, hogy aránytalanul csökkenti a magas bérű munkavállalók jövedelmét. Ezek az eredmények akkor is szilárdak maradnak, ha figyelembe vesszük a piaci erő és a technológiai változás alternatív forrásait.

Az elemzés továbbá azt mutatja, hogy ezek a hatások a nagyvárosi régiókban jelentősen erősebbek. A munkaerő-piaci erőfölény nagyobb bércsökkentő hatást gyakorol a városi munkaerőpiacokon, különösen a magasan képzett és jól fizetett munkavállalók körében, ami arra utal, hogy a városok a sűrű munkaerő-piaci verseny és a munkavállalók gyengébb alkupozíciója révén fokozzák a monopszonisztikus nyomást. Ezek az eredmények új perspektívát nyújtanak az urbanizáció és a munkaerő-piaci erőfölény közötti kölcsönhatásra, kiemelve azokat a mikroökonómiai mechanizmusokat, amelyek révén a nagyvárosi munkaerőpiacok alakítják a bérkialakulást.

Összességében a tanulmány a munkaerő-piaci hatalmat azonosítja az európai regionális bérkülönbségek egyik fontos, de gyakran figyelmen kívül hagyott meghatározó tényezőjeként. Az eredmények arra utalnak, hogy a területi egyenlőtlenségek csökkentéséhez nemcsak újraelosztási politikákra van szükség, hanem erősebb munkaerő-piaci intézményekre is, ideértve a kollektív tárgyalásokat és a végrehajtási mechanizmusokat, valamint olyan helyspecifikus politikákra, amelyek megőrzik a városok termelékenységi előnyeit, miközben korlátozzák a munkáltatók túlzott bérmegállapítási hatalmát.

Introduction

In recent decades, concerns about economic inequality have re-emerged as a central issue in both academic and policy debates (De Loecker, Eeckhout, Unger 2020; Karabarbounis 2024; Acemoglu, Lelarge, Restrepo 2020; Moll, Rachel, Retsrepo 2022; Autor 2022; ILO 2024; Chancel et al. 2026). A vast literature has consistently documented persistent and substantial gaps across individuals, social groups, places, and countries (Chancel et al. 2026). Despite two centuries of sustained growth, in fact, the last four decades have seen substantial gains accrued to a relatively small segment of individuals, communities, and places, while the majority has not benefited proportionally from rising aggregate wealth (Feldman, Guy, Iammarino 2021).

In this context, the evolution of wage inequalities has attracted particular interest, given its direct implications for social and economic cohesion (Allen 2024; Autor 2022), with attention increasingly shifted to the investigation of the mechanisms shaping such uneven economic landscapes (Piketty 2014; Autor 2022; Chancel et al. 2026).

A large body of work has focused on technological change and globalisation, emphasising the role of automation, offshoring, and skill-biased technological change in shaping wage structures and imbalances (Autor, Levy, Murnane 2003; Autor, Dorn 2013; Acemoglu, Restrepo 2019, 2022). This stream of studies has consistently documented the erosion of the middle-income class, the stagnation of median earnings, the polarisation of wages, and the widening of interpersonal inequalities, often described as the great divergence (Moretti 2012; McAfee, Brynjolfsson 2017).

At the same time, more recent contributions have highlighted the growing importance of market imperfections in both product and labour markets, and in particular the role of employer wage-setting power (monopsony) in influencing wage levels and labour market outcomes (Manning 2021; Card 2022; Dube et al. 2020). Evidence on the effects of product market power on income and wage inequalities is rapidly accumulating (Autor et al. 2020; Syverson 2019; De Loecker, Eeckhout, Unger 2020; Barkai 2020), but much less is known about the implications of labour market power. Moreover, existing studies have primarily examined how employer concentration and monopsony power affect labour

market outcomes in terms wage levels, hiring, and employment stability, but comparably less attention has been devoted to their impact on wage dispersion within local labour markets (Azar et al. 2020; Bassanini et al. 2024, 2023; Martins, Melo 2024; Dondini et al. 2024; Marinescu, Ouss, Pape 2021; Popp 2024; Benmelech, Bergmand, Kim 2022; Manning 2021; Card 2022; Dube et al. 2020; Mertens 2022, 2023).

This paper tries to fill this gap by investigating the relationship between labour market power and wage inequalities across European regions. In particular, it addresses three interrelated research questions: (i) does labour market power systematically affect wage dispersion within regions? (ii) do these effects differ across the wage distribution, i.e., between low-, median-, and high-wage workers? (iii) are these relationships mediated by the spatial structure of labour markets, and more specifically by the distinctive characteristics of metropolitan regions?

In replying to these questions, the paper introduces two main novelties. On conceptual grounds, the paper elaborates on the mechanisms that may lead to differ pressure on and compression of high and low wages and whether they differ across urban vs non-urban settings, proposing that especially high-wage workers and metropolitan areas experience the largest markdown penalty. On empirical grounds, using data from the CompNet database at the NUTS2 regional level, the paper offers a novel overview on wage disparities in the European Union, where inequality levels are comparatively moderate by global standards (ILO 2024; Chancel et al. 2026) but still marked spatial heterogeneity persists across and within countries (OECD 2024; Rodríguez Pose et al. 2024).

Previewing the results, the analysis developed in the paper shows that higher labour markdowns are systematically associated with lower wages throughout the distribution, with the largest penalties emerging at upper percentiles and in metropolitan regions, possibly due to intense worker competition, weaker collective action, and greater employer discretion.

The remainder of the paper is organised as follows. Section 2 reviews the literature and elaborates the research questions. Section 3 illustrates recent trends on wage inequality across European regions. Section 4 presents the empirical approach and describes the variables while Section 5 discusses the results. Section 6 concludes with some reflections on the implications for policy.

Labour market power and wage inequalities in space

Labour market power, intended as wage-setting power, alters the link between workers' marginal productivity and their remuneration enabling firms operating in uncompetitive settings to set wages below marginal productivity; this wedge is typically called in the literature as wage markdown (Manning 2021; Card 2022).

Labour markdowns have direct implications for wage inequality. Labour market concentration, search frictions, or mobility constraints all concur to weakening workers' outside options, to increasing the room for exerting labour market power and thus to systematically depressing wages across the distribution. More importantly, these effects are unlikely to be uniform: the degree to which different workers can resist wage suppression varies depending on skill levels, bargaining institutions, and job characteristics. As a result, labour market power not only lowers average wages, but also reshapes the dispersion of wages within local labour markets.

The theoretical relationship between labour market power and wage inequality, however, remains ambiguous, and dependent on the balance between two main competing mechanisms.

On the one hand, monopsony power can reduce wage inequality through a compressive mechanism. If firms are able to set wages below marginal productivity, and particularly if this effect is stronger for high-productivity or high-wage workers, the outcome may be a reduction in upper-tail wages and therefore a narrowing of wage dispersion. Put differently, monopsony can equalise downwards, compressing wage gaps by disproportionately affecting top earners. Minimum wages, collective bargaining, and wage floors limit downward adjustments at the bottom of the wage distribution (Martins, Melo 2024). At the same time, evidence suggests that labour market power tends to be strongest in large, productive, and high-paying firms (Mertens 2023; Goolsbee, Syverson 2023).

On the other hand, labour market power may increase inequality. Workers with weaker bargaining positions–due to lower skills, precarious contracts, or fewer outside options–are likely to be subject to stronger wage suppression, whereas more mobile or highly skilled workers may retain some bargaining power (e.g., through rent-sharing mechanisms as in Card 2022). In this case, uncompetitive wage-setting behaviours can lead to amplify wage dispersion by unevenly affecting different segments of the workforce. Moreover, if labour market power depresses labour shares and reallocates surplus towards firms, the resulting decline in wage growth may disproportionately affect median and lower-percentile workers, contributing to widening interpersonal inequalities.

Therefore, the balance between these two opposite forces and which workforce segment is most affected by monopsonistic behaviours determine the overall effect on wage inequality.

Importantly, labour markets are characterised by an inherently spatial dimension, where geographic frictions, such as commuting costs, search costs, mobility constraints, and institutional contexts, contribute to define the boundaries of local labour markets (Webber 2015; Manning 2021; Manning, Petrongolo 2024). As a result, monopsony power is fundamentally exerted at the local level, and its intensity depends on regional labour market thickness, employer concentration, and matching efficiency. In local labour markets, firms

may recognize their influence on wages and employment and maximize profits by restricting hiring to keep wages low (Berger, Herkenhoff, Mongey 2021). A rapidly growing empirical literature documents substantial employer concentration in local labour markets and links it to lower wages, reduced hiring, and weaker job security across a wide range of countries (e.g. Manning, Petrangolo 2024 on the UK; Marinescu, Ouss, Pape 2021 on France; Popp 2024 on Germany; Azar, Marinescu, Steinbaum 2022; Dube et al. 2020; Rinz 2022 on US; Martins, Melo 2024 on Portugal; Caselli, Mondolo, Schiavo 2023 on Italy; Dodini et al. 2024 on Norway; Soderqvist, Eklund 2024 on Sweden; Bassanini et al. 2024 on a sample six European countries).

Importantly, urban labour markets exhibit distinctive features that may shape the relationship between productivity and wages (Duranton, Puga 2004, 2020; Puga 2010). Although cities benefit from agglomeration economies, superior matching and a well-established urban wage premium, they are also characterised by intense competition for desirable jobs, career progression and professional status. In such environments, workers, particularly younger and highly educated ones, may supply effort beyond productivity requirements in order to signal ability and maintain visibility, resulting in longer working hours, greater availability and increased flexibility, generating an "urban rat race" (Rosenthal, Strange 2008). Moreover, weaker interpersonal ties and lower levels of trust can limit collective bargaining capacity, reduce workplace autonomy and increase employers' wage-setting discretion (Lunardon 2024). Consequently, urban workers may accept wages below their marginal productivity in exchange for career opportunities, learning effects and other non-pecuniary advantages. These features may amplify monopsonistic forces in urban labour markets, especially among high-skilled workers, thereby generating stronger effects on wage compression and inequality.

By focusing on the European regions case, the empirical analysis aims at documenting whether labour market power contributes to a reduction of wage levels and inequalities, and whether these effects are enhanced especially in cities.

Wage inequalities in EU regions

Existing studies have richly proved the widening of the wage gaps and polarisation among workers groups, for example between the most and the least educated and skilled workers or between routine vs non-routine jobs, and the concomitant reduction in real (median) wages (Acemoglu, Restrepo 2022; Moll, Rachel, Restrepo 2022), a phenomenon frequently related to computerisation, automation and, partly, the diffusion of artificial intelligence (Autor, Levy, Murnane 2003; Autor, Dorn 2013; Goos, Manning, Salomons 2009, 2014; Acemoglu, Restrepo 2019; Acemoglu 2025). Yet, recent evidence points to a moderate narrowing of wage gaps

in many economies (ILO 2024). Starting with the 2020s, in fact, global wage inequalities have entered a phase of moderate decline, particularly in advanced and Western economies (ILO 2024). In Europe, this reduction has been partly driven by relatively stronger real wage growth compared with other developed economies, especially in the years preceding the pandemic. Wage growth has been faster in the bottom decile of the distribution and progressively slower in the middle and upper deciles, resulting in wage convergence (Zwysen 2024).

In the effort to reconcile these divergent trends, Figures 1 to 3 extend these country level findings to European NUTS2 regions. By balancing economic relevance and data availability,[1] the NUTS2 level of analysis provides an appropriate spatial scale to capture the functioning of labour markets and wage inequalities, consistent with a very rich stream of studies (Ioramashvili 2024; Caselli, Mondolo, Schiavo 2023; Lenzi, Panzera 2025).[2] Specifically, Figure 1 illustrates the annual compound growth rates of the regional 10th percentile and 90th percentiles (Figure 1) between 2009 and 2019 and the evolution of absolute wage gaps and relative ratios (Figures 2 and 3).

These indicators are based on the 9th vintage edition of the CompNet database (Mertens 2023). The Compnet dataset used in this paper covers the population (or large and representative sample) of non-financial corporations[3] with at least one employee,[4] with raw data retrieved from national statistical offices and business registers and next released with different levels of aggregation (e.g. country, sector, region). Lack of data at the NUTS2 level in the Compnet dataset or in the variables used in the following empirical analysis, limit the analysis to 18 countries out of the 22 monitored in Compnet, with the unfortunate exclusion of Germany, Netherlands, Switzerland and UK.[5]

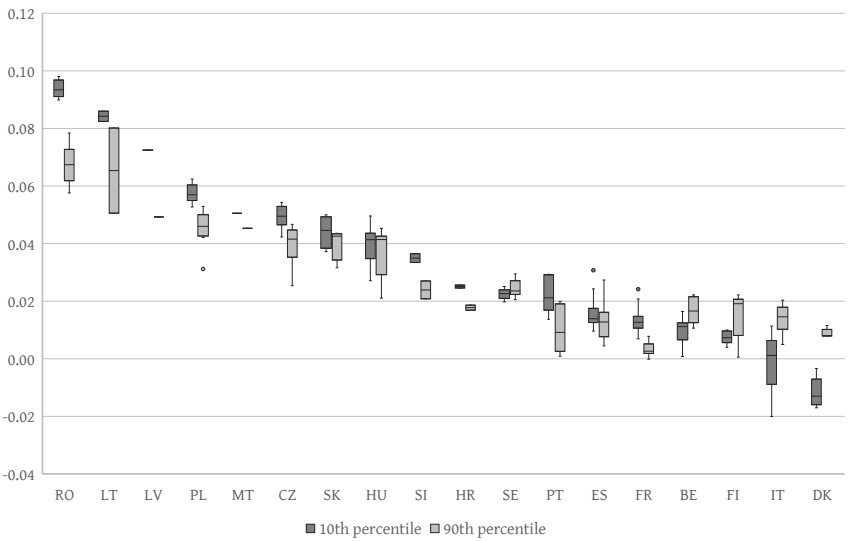
Even if Compnet does not offer the possibility to track labour costs of each workers nor of specific groups of workers (e.g. by education, skills, or routine content), Compnet provides information on the distribution of labour costs (i.e. moments and different percentiles of the indicators distribution) across firms within regions, thus capturing wage dispersion in the regional workforce. Specifically the regional 10th and 90th wage percentiles are obtained by identifying the 10th and 90th wage percentile of each firm and, next, by computing employment-weighted averages across firms within each NUTS2 region.

In details, Figure 1 shows the evolution of the 10th and 90th wage percentile between 2009 and 2019 in EU NUTS2 regions, grouped by countries ranked by decreasing growth rate of 10th wage percentile. The graph therefore combines three interesting information: 1) the growth rate of the 10th and 90th percentiles of regional wages, 2) the within-country regional heterogeneity in the growth rate of different regional wage percentiles and 3) cross-country variation in these growth rates.

On average, bottom decile wages increased over time in most regions with a few exceptions, including all Danish regions and selected Italian ones where

wage growth rates remain negative. Top decile wages also increased, although at a more modest pace, a pattern consistent with country level evidence (ILO 2024; Zwysen 2024). Quite interestingly, these trends have also a country dimension. Growth rates of both bottom and top wages have been particularly high in Eastern European countries (e.g. Romania and Poland) while growth rates have been feebler in Western European countries. More generally, spatial gaps in growth rates of both bottom and top wages (as shown by the size of bars in the graph) do not present particularly heterogenous patterns within country.

Figure 1: Regional wage growth - annual compound growth rate 2009-2019, by country and wage percentile
Regionális bérnövekedés – éves összetett növekedési ráta 2009–2019 között, országok és bérpercentilisek szerint



Note: The units of analysis are EU NUTS2 regions.
Source: Authors' construction

The convergence trend emerging from Figure 1 confirms that the EU performs relatively well globally in terms of inequality (Chancel et al. 2022, 2026); yet, this coexists with enduring wage gaps within and across EU regions. Specifically, Figures 2 and 3 display *absolute* and *relative* wage ratios, measured respectively as difference (Figure 2) and ratio (Figure 3) between the regional 10th and 90th wage percentiles (e.g. D9/1) in 2009 and 2019, with regions grouped by country ranked by decreasing wage differences (ratios, respectively).

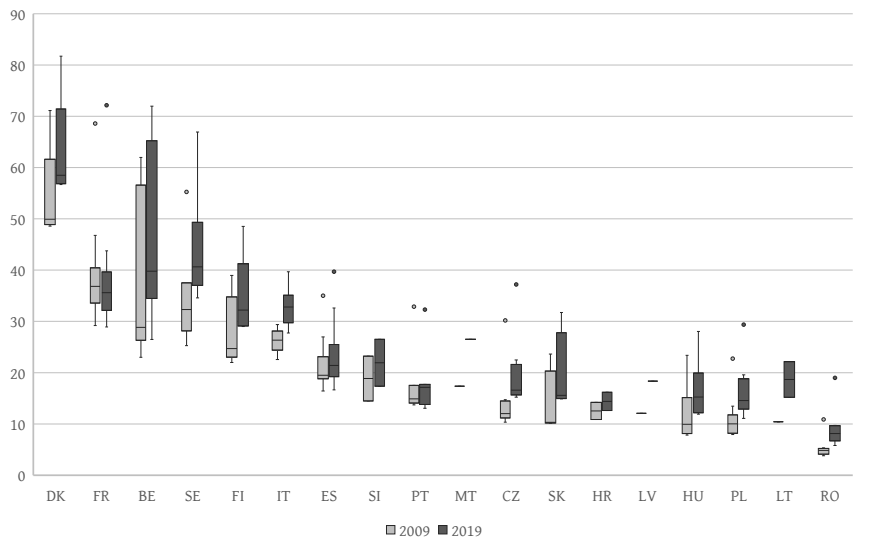
Both measures are useful to understand inequality patterns. While Eastern European countries tend to rank lower in terms of absolute differences with respect to Western countries, they tend to rank high in terms of relative

differences. In short, large absolute wage differences can coexist with moderate relative gaps (e.g. Belgium) and vice versa (e.g. Hungary and Poland), likely reflecting the average wage structure in the two blocks of countries: higher wages in Western countries and lower wages in Eastern ones.

Moreover, Figures 2 and 3 highlight the existence of outlining regional cases that significantly depart from the national average behaviour, as also summary statistics in the Appendix (Table A2) reveal. These regions are likely to experience substantial wage dispersion and appear in both high and low wage countries, possibly in large metropolitan areas or capital cities (Kemeny, Petralia, Storper 2022). These findings align with global evidence linking urbanization to increased within place inequality (ILO 2024; Chancel et al. 2026).

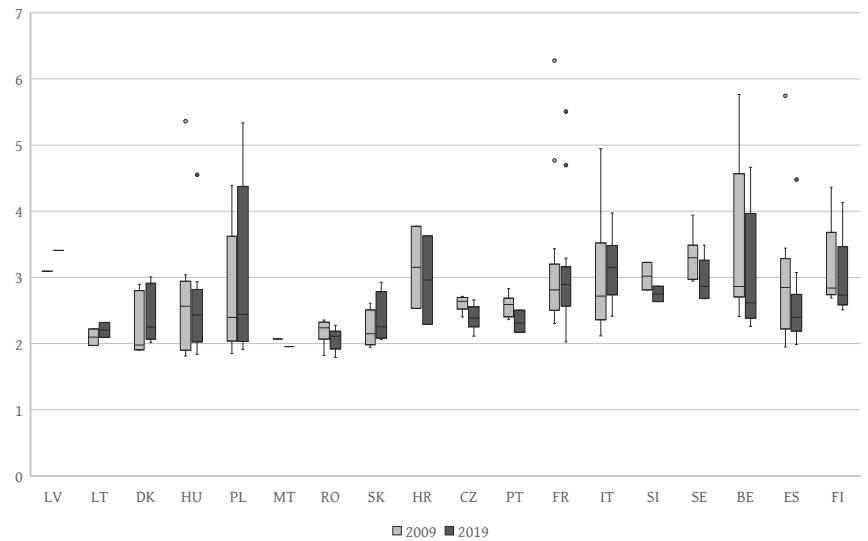
Taken together, the joint reading of Figures 1 to 3 suggests a wage convergence trend, in a pattern of spatially heterogeneous wage gaps.

Figure 2: Difference between top (90th percentile) and bottom (10th percentile) wages in EU NUTS regions, grouped by country (2009 and 2019)
A legmagasabb (90. percentilis) és a legalacsonyabb (10. percentilis) bérek közötti különbség az EU NUTS-régióiban, országok szerint csoportosítva (2 009 és 2019)



Note: The units of analysis are EU NUTS2 regions.
Source: Authors' construction

Figure 3: D9/1 ratio (90th-to-10th wage ratio) in EU NUTS regions, grouped by country (2009 and 2019)
A D9/1 arány (a 90. és a 10. legmagasabb bér aránya) az EU NUTS-régiókban, országok szerint csoportosítva (2009 és 2019)



Note: The units of analysis are EU NUTS2 regions.
Source: Authors' construction

The econometric approach

Examining the link between wage inequality and labour market power requires careful consideration of how both concepts are measured, particularly at the regional level.

Concerning wage inequalities, the analysis adopts an encompassing perspective, using a broad set of indicators: (i) differences and ratios between the 90th and 10th percentiles (P90–P10; D9/1), between P90 and the median (P90–P50; D9/5), and between the median and P10 (P50–P10; D5/1); and (ii) levels at multiple points of the distribution (P10, P25, P50, P75, P90, P95, P99). All measures, derived from Compnet database, are computed as regional employment-weighted averages across firms in each NUTS2 region, as described in Section 3.

Regarding the measures of market power, the paper relies again on the Compnet database that allows monitoring multiple dimensions of competition on labour markets.

The main indicator is the labour markdown, which accounts for the wedge between wage and the marginal revenue product of labour, that regional firms are, on average, able to implement. In details, the labour markdown measure at

the NUTS2 level is estimated in Compnet at the firm level and next aggregated at the regional level by computing employment-weighted averages within NUTS2 regions. The markdown estimation at the firm level is derived and discussed in detail in Mertens (2022, 2023) and has been obtained in the frame of a Cobb-Douglas production function by applying the Ackerberg, Caves, Frazer (2015) method. The estimation of labour markdowns based on CompNet data at the NUTS2 level is not free of limitations and potential measurement errors. First, the estimation of the marginal revenue product derives from production-function estimates obtained via the Ackerberg, Caves, Frazer (2015) approach, which, despite addressing functional-dependence issues, remains sensitive to identification assumptions (Shanks 2024). Second, the adoption of a Cobb–Douglas specification imposes unit elasticity of substitution and constant output elasticities, potentially misrepresenting heterogeneous technologies across firms, sectors, and regions. Third, the aggregation of firm-level data into regional indicators may introduce an aggregation bias, as markdowns are nonlinear functions of micro-level variables and may be distorted by composition effects. Despite these limitations, to our knowledge, Compnet is the only source complementing information on labour market concentration with indicators capturing labour market power exercised through local employment relationships.

As an additional labour market control, the Herfindahl–Hirschman Index (HHI) of employment shares across regional firms is included to separate the effect of market concentration from markdowns and from product market power (e.g. Azar et al. 2020; Azar, Marinescu, Steinbaum 2022; Marinescu, Ouss, Pape 2021; Manning, Petrangolo 2024; Bassanini et al. 2024).

A set of panel regressions was estimated to assess how labour market power relates to (i) inequality measures and (ii) wage levels across percentiles. This allowed testing whether markdowns are associated with widening or narrowing inequality (Eq. 1) and whether upper vs. lower parts of the wage distribution are differentially affected (Eq. 2). Moreover, the interaction between the markdown measure with the dummy flagging metropolitan regions allowed exploring whether urban contexts are especially prone to unfavourable labour market conditions. In this context, metropolitan regions are defined as those with a share of population in Eurostat defined metropolitan areas above the 90th percentile threshold.

$$\begin{aligned}&\text{Wage inequalities}_{r,t}\\&= \alpha + \beta_1 \text{ labour market power}_{r,t}\\&+ \beta_2 \text{ metro}_{r,} + \beta_3 \text{ labour market power}_{r,t} \text{ x metro}_r + \beta_4 X_{r,t}\\&+ \text{country FE x year FE} + \varepsilon_{r,t}\end{aligned} \qquad 1$$

$$\begin{aligned}&\text{Wage percentiles (from 10th to 99th)}_{r,t}\\&= \alpha + \beta_1 \text{ labour market power}_{r,t}\\&+ \beta_2 \text{ metro}_r + \beta_3 \text{ labour market power}_{r,t} \text{ x metro}_r + \beta_4 X_{r,t}\\&+ \text{country FE x year FE} + \varepsilon_{r,t}\end{aligned} \qquad (2)$$

where *r* indicates the NUTS2 region and t the year from 2009 to 2020. The different wage percentiles refer respectively to the 10th, 25th, 50th, 75th, 90th, 95th and 99th percentile of the labour cost averaged across firms in a NUTS2 region. Estimates have been obtained by weighted regressions accounting for the initial levels of employment to control for the different size of regions in the sample, with standard errors clustered at the NUTS2 level and country by year fixed effects. Ideally, a regional fixed-effect specification would be preferable. However, the time-invariant nature of the metropolitan dummy (and other explanatory variables) prevented to follow this approach. At the same time, country-by-year fixed effects provide a flexible and meaningful way to control for cross-country differences in institutional settings, labour market regulations, wage-setting mechanisms, macroeconomic conditions and shock, likely to be time-varying and to influence both wage levels and wage dispersion. By absorbing all national-level shocks and trends, this specification allows estimating differences across regions within the same country and year, thereby reducing concerns related to omitted variable bias driven by unobserved country- and time-level heterogeneity.

The term $X_{r,t}$ includes a set of control variables aimed at capturing:

i. some standard control variables accounting for the structure of the regional labour force in terms of education, gender balance, migration status, skill level, age (see for comparable approaches Azar et al. 2020; Bassanini et al. 2023, 2024; Martins, Melo 2024; Dondini et al. 2024; Marinescu, Ouss, Pape 2021; Popp 2024; Benmelech, Bergman, Kim 2022);
ii. key variables accounting for possible labour substitution effects and, thus, likely to exert a downward pressure on wages, uneven across the distribution, namely regional capacity for internationalisation and regional automation intensity (Acemoglu, Restrepo 2022; Autor, Dorn 2013);
iii. additional sources of market imperfections, namely firms market power in product markets captured through a mark-up measurwe,[6] which may contribute to a downward pressure on wages across the distribution, primarily through a reduction of the labour share (Mertens 2022, 2023; De Loecker et al. 2018).

All regressions include also a set of variables measuring regional employment share in 1-digit NACE Rev2.2 sectors. All variables are measured at year t, with the exception of the metro dummy and the trade intensity variable which are time-invariant. Variables descriptions and summary statistics are provided in the Appendix (Tables A1 and A2) while the next section presents and discusses the results.

Results and discussion

Table 1 reports the output of the estimation of equations 1 and 2. Quite interestingly, results present a remarkable stability in terms of sign and magnitude of the estimated coefficients while confirming some general trends highlighted in Section 2 and robust findings in the literature.

First, the coefficient on labour markdown is consistently negative for wage levels across percentiles, with larger penalties at higher percentiles. This implies that stronger employer wage setting power compresses the wage structure from above (i.e., depresses upper tail wages more than lower tail wages), thereby reducing both absolute and relative inequality measures primarily in the upper half of the wage distribution. Still, it is worth noticing that the markdown measures estimated in Compnet can introduce non-classical measurement error, bearing implications for the econometric estimation of the respective coefficient. On the one hand, attenuation bias can be present due to the aggregation of firm-level markdowns to the NUTS2 level and the reliance on production-function-based marginal products likely tempering cross-regional variation. On the other, upward bias is equally likely due to common omitted factors affecting both markdowns and wage inequality such as productivity, sectoral composition, and institutional settings, generating potential upward bias through common omitted factors. Moreover, the estimated relationship may partly reflect compositional and sorting effects, particularly the spatial concentration of high-productivity or "superstar" firms, rather than pure monopsony power. Lastly, the close accounting link between markdowns, labour shares, and wage gaps raises the possibility of mechanical correlations. Overall, these issues imply that the estimated coefficient should be interpreted as a reduced-form association rather than a causal estimate of labour market power on inequality.

Irrespective of the indicator considered, wage inequalities tend to be higher in cities, in internationalised and more educated regions; these dimensions matter for the upper half of the distribution more than for the bottom half being the respective coefficients greater when estimating the difference between the 90th and 50th percentile and the D9/5 ratio than when estimating the difference between the 50th and 10th percentile and the D5/1 ratio. This is consistent with the increasing premium of cities, international exposure and education at higher wage percentiles.[7] Differently, labour market participation of foreign-born and females present a more heterogeneous outlook. While they are positively associated with wage levels, with rates increasing toward the upper tail, they are also associated with widening absolute wage gaps but narrowing relative wage gaps especially in the lower half of the distribution. This may signal a situation of faster wage growth in the bottom deciles rather than in the top ones, leading to more equality in relative terms, still in a context of widening absolute differences. These conclusions are consistent with Global Wage Report evidence

(ILO 2024) on over-representation of these groups among low-wage workers and on wage gaps with respect to males and natives especially in the bottom wage deciles. Moreover, a higher share of elementary occupations and an older workforce are negatively associated with wages at all percentiles, leading to a reduction of wages gaps both in absolute and in relative terms.

Importantly, labour market concentration and automation penalise wage levels across the distribution whereas markup shows a more unstable behaviour, looking favourable for very top earners (95th and 99th wage percentile).

The interaction between the markdown variable and the metropolitan region dummy highlights that markdown penalties are especially large in metropolitan contexts and the amplification increases toward the upper percentiles. This aligns with the urban rat-race mechanism (Rosenthal, Strange 2008) whereby intense worker rivalry and weaker social ties reduce collective action, enhance employer discretion, and heighten firms' wage setting power (Lunardon 2024). This finding is also consistent with evidence that high paying firms often exert greater labour market power, implying larger markdowns at the top of the distribution (Mertens 2023).

Figure 6 summarises these results by plotting the average marginal effects of labour markdown on wage levels (P10-P90) in metropolitan and non-metropolitan regions calculated on the estimates presented in Table 1. Quite interestingly, markdown penalties are uniformly negative and systematically larger in metros. Some back-of-the-envelope calculations indicate that the labour markdown penalty of urban areas rises by 8.5 percentage points when moving from the 25th to the 75th wage percentile. with the gap widening especially from the median to the upper tail (50th to 90th percentile).

Table 1: Labour market power and wage inequalities in metropolitan vs non-metropolitan regions
Munkaerő-piaci erőviszonyok és bérkülönbségek a nagyvárosi és a nem nagyvárosi régiókban

Variables	*Wage differences*			*Wage ratio*		
	90th - 10th	*90th – 50th*	*50th -10th*	*D9/1*	*D9/5*	*D5/1*
Labour markdown	-3.6848***	-2.3593***	-1.3255***	-0.0165	-0.0171	0.0008
	(0.713)	(0.548)	(0.272)	(0.080)	(0.021)	(0.024)
Metro region	8.4762***	6.2691***	2.2071***	0.4040*	0.1600**	0.0835
	(2.352)	(1.818)	(0.756)	(0.209)	(0.067)	(0.051)
Labour markdown x metro region	-2.2197**	-1.6076**	-0.6121*	0.0546	0.0038	0.0108
	(0.872)	(0.661)	(0.345)	(0.099)	(0.032)	(0.018)
Labour market concentration	-44.9803	-31.7128	-13.2675	5.2841**	0.9513	1.5793*
	(30.290)	(24.945)	(9.439)	(2.100)	(0.701)	(0.812)
Markup	0.0210**	0.0197***	0.0014	-0.0006	0.0001	-0.0003
	(0.009)	(0.007)	(0.003)	(0.001)	(0.000)	(0.000)
Robot density	-1,462.6**	-667.6	-795.0***	83.10	24.25	25.76
	(607.999)	(504.392)	(190.806)	(62.676)	(20.804)	(18.921)
Education	2.4745	1.5159	0.9586	2.2055***	0.3717	0.6797***
	(11.052)	(8.288)	(4.570)	(0.790)	(0.340)	(0.221)

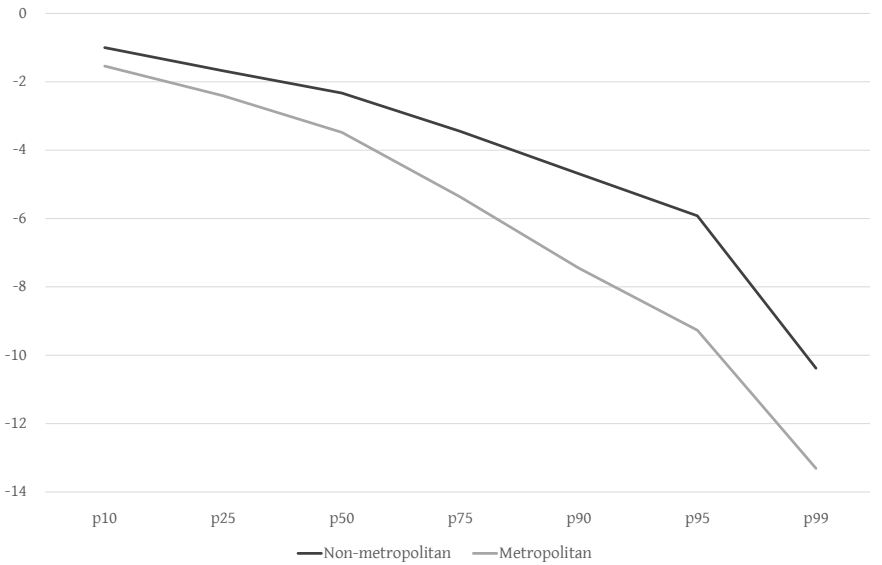
Variables	*Wage differences*			*Wage ratio*		
	90th - 10th	*90th – 50th*	*50th -10th*	*D9/1*	*D9/5*	*D5/1*
Foreign employment	44.6628***	30.9859***	13.6769***	-2.9597***	-0.7427**	-0.4956**
rate	(9.683)	(7.671)	(3.735)	(1.028)	(0.334)	(0.247)
Female employment	8.1964	-5.1242	13.3206	-6.6260***	-1.1524*	-2.3941***
rate	(20.146)	(14.118)	(8.133)	(1.825)	(0.626)	(0.598)
Elementary occupation	-16.7670	-14.8369	-1.9300	-0.6621	-0.2294	0.0630
	(13.438)	(10.937)	(3.414)	(1.035)	(0.389)	(0.312)
Median age	-0.3493	-0.2470	-0.1023	-0.0365*	-0.0139**	-0.0046
	(0.231)	(0.178)	(0.071)	(0.022)	(0.007)	(0.006)
Trade exposure	4.9428*	3.2710	1.6718**	0.5738*	0.1585*	0.1043
	(2.634)	(2.008)	(0.715)	(0.324)	(0.092)	(0.078)
Constant	31.9143**	16.1970	15.7173***	7.0139***	2.5134***	3.0214***
	(13.870)	(11.144)	(4.909)	(1.106)	(0.404)	(0.317)
R-squared	0.968	0.877	0.944	0.903	0.981	0.915

Variables	*Average wage*						
	10th	*25th*	*50th*	*75th*	*90th*	*95th*	*99th*
Labour markdown	-1.0009***	-1.6789***	-2.3263***	-3.4517***	-4.6857***	-5.9174***	-10.3820***
	(0.327)	(0.452)	(0.492)	(0.637)	(0.870)	(1.105)	(2.903)
Metro region	0.8747	1.6021*	3.0819**	6.1044***	9.3510***	11.5482***	14.7674**
	(0.687)	(0.953)	(1.281)	(1.947)	(2.672)	(3.346)	(7.372)
Labour markdown x metro region	-0.5417*	-0.7165*	-1.1538*	-1.9143**	-2.7614***	-3.3476***	-2.9236
	(0.291)	(0.405)	(0.585)	(0.818)	(0.980)	(1.127)	(3.404)
Labour market concentration	-21.0589	-31.7834*	-34.3264*	-47.7584*	-66.0392*	-83.5194	-97.0863
	(13.388)	(18.705)	(19.858)	(26.795)	(39.088)	(50.639)	(117.979)
Markup	-0.0040	-0.0051	-0.0026	0.0041	0.0171	0.0332**	0.1456***
	(0.005)	(0.007)	(0.007)	(0.009)	(0.011)	(0.014)	(0.042)
Robot density	-1,308.8***	-1,964***	-2,103.8***	-2,409.6***	-2,771.4***	-3,043.7***	-5,433.6***
	(279.744)	(414.959)	(401.640)	(527.503)	(766.225)	(1,005.084)	(1,906.052)
Education	3.0600	0.2178	4.0187	5.4080	5.5346	0.7748	-25.6438
	(4.624)	(7.059)	(8.278)	(10.026)	(13.084)	(16.103)	(32.311)

Variables	*Average wage*						
	10th	*25th*	*50th*	*75th*	*90th*	*95th*	*99th*
	(4.624)	(7.059)	(8.278)	(10.026)	(13.084)	(16.103)	(32.311)
Foreign employment	2.1101	3.3905	15.7871*	30.7835***	46.7729***	58.5142***	94.2768***
rate	(5.494)	(8.077)	(8.146)	(9.105)	(11.275)	(14.086)	(27.381)
Female employment	35.6332***	50.4036***	48.9538***	42.5236**	43.8295*	49.5201	42.4713
rate	(10.012)	(14.850)	(15.992)	(18.709)	(25.804)	(31.913)	(63.580)
Elementary occupation	-6.8096	-5.1431	-8.7396	-16.9157	-23.5766	-28.8240	-44.7883
	(4.597)	(5.800)	(6.881)	(10.526)	(16.237)	(21.463)	(41.008)
Median age	-0.0564	-0.1316	-0.1587	-0.2641	-0.4057	-0.5382	-1.3964**
	(0.080)	(0.110)	(0.126)	(0.172)	(0.265)	(0.341)	(0.641)
Trade exposure	1.2621**	1.9793**	2.9339***	4.3872**	6.2050**	7.4347**	11.9447**
	(0.559)	(0.790)	(1.071)	(1.753)	(2.838)	(3.650)	(6.012)
Constant	19.2712***	29.0218***	34.9885***	41.7733***	51.1854***	59.3951***	112.9789**
	(6.781)	(10.022)	(10.423)	(12.259)	(17.558)	(22.701)	(43.784)
R-squared	0.984	0.983	0.987	0.985	0.980	0.976	0.960

*Note: N= 149 x 8 (1162). *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the NUTS2 level in parentheses. Country by year fixed effects included.*
Source: Authors' construction

Figure 4: Average marginal effects of labour market power on wage levels in metropolitan vs non-metropolitan regions
A munkaerő-piaci erő átlagos marginális hatása a bérszintekre nagyvárosi és nem nagyvárosi régiókban



Note: all average marginal effects are significant at conventional level, as much as their pairwise comparison.

Final remarks

This paper has examined the patterns and drivers of wage inequalities across European regions through a regional lens, with particular attention to the role of labour market power and its heterogeneous expression across metropolitan and non metropolitan contexts. Three key conclusions emerge.

First, although wage gaps have shown a moderate downward trend in many advanced economies, European regions continue to exhibit substantial heterogeneity in both wage levels and wage dispersion over time. Differences across countries are coupled with persistent inter regional divides, especially in metropolitan areas. The urban wage premium-reflecting differentiated returns to skills, education, and internationalisation-remains a key driver of widening wage gaps between high and median wage earners.

Second, the findings highlight a systematic and robust effect of labour market power, proxied by labour markdowns, on wage outcomes. Higher markdowns are associated with lower wages at all points of the wage distribution, with the largest penalties at the top. Employer wage setting power thus tends to compress

the wage structure from above, narrowing inequality through the downward pressure on high earning workers, rather than through any meaningful improvement in conditions at the bottom. This result is highly stable across specifications and remains unaffected by the inclusion of controls for product market power, labour market concentration, or exposure to robotisation-each typically associated with uncompetitive market behaviour in the literature.

Third, metropolitan regions amplify these dynamics. Labour markdowns exert a stronger wage depressing effect in urban settings, consistent with the urban rat race mechanism described in the literature, whereby intense worker rivalry, weak social ties, and reduced collective action increase employer discretion in wage setting. In these contexts, monopsonistic pressures are particularly acute among higher paid and higher skilled workers, who are more exposed to competitive signalling dynamics. Cities may therefore become environments where wage setting frictions and employer power are most pronounced, especially in the upper segments of the labour market. This provides a novel interpretive lens on why labour market power has especially strong wage effects in metropolitan regions and which emphasises the micro foundations of urban labour competition.

In conclusion, the results underline how the characteristics and spatial organisation of labour markets shape wage inequalities across and within European regions. Labour market imperfections emerge as an important, yet often underappreciated, driver of regional wage disparities. The spatially asymmetric effects of labour markdowns across the wage distribution indicate that reducing wage inequalities will require coordinated policy actions. These include not only traditional redistributive tools, but also the strengthening of labour market institutions, such as collective bargaining systems and enforcement mechanisms. At the same time, place sensitive interventions are needed to ensure that metropolitan labour markets remain engines of economic opportunity while avoiding excessive competitive pressures that erode worker bargaining power. Integrated and well targeted policies are thus essential for promoting decent work, supporting wage growth, reducing regional divides, and ultimately enhancing Europe's social sustainability and territorial cohesion.

Notes

1 Data availability at more granular spatial scales represent an important constraint especially for what concerns the control variables used in the econometric analysis.

2 Even if labour markets are inherently local, their effective functioning often extends beyond narrowly defined commuting zones, particularly in European contexts characterised by polycentric settlement structures and integrated regional economies.

3 The public sector is not covered in the CompNet dataset. While this excludes a non-negligible share of employment, it does not look problematic here. The analysis focuses on market

power—i.e. outcomes driven by profit-maximising firms operating under competitive pressures. In contrast, public sector organisations are governed by non-market objectives and institutional wage-setting, so the mechanisms underlying markups, wage-setting, and firm competition do not apply in the same way. Restricting the analysis to the market sector therefore enhances internal consistency, as it isolates the domain in which market power is meaningfully defined and empirically observed.

4 The number of employees is measured in headcounts.

5 Six EU countries are not covered by Compnet, namely Austria, Bulgaria, Cyprus, Estonia, Greece, Ireland, Slovenia.

6 The markup measure at the NUTS2 level is derived in Compnet from firm level data and next aggregated at the regional level by computing employment-weighted averages within NUTS2 regions. The markup estimation at the firm level is derived and discussed in detail in Mertens (2022, 2023) and has been obtained in the frame of a Cobb-Douglas production function by applying the Ackerberg, Caves, Frazer (2015) method. The markup measure therefore is able to account for the degree of market power that regional firms on average are able to exert in their relevant markets, regardless of their spatial reach (local, domestic, European if not international).

7 Education, international exposure and skill level are well documented characteristics of cities. Even if these dimensions are potentially highly correlated, unreported VIF statistics, available upon request, exclude serious multicollinearity issues in the estimates displayed in Table 1.

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Appendix

Table A1: Variables Description / *A változók leírása*

Variable	*Description*	*Data source*
Wage inequalities	Difference (respectively, ratio) between wage percentiles of the labour cost per employee, e.g. 90th percentile vs 10th percentile, 90th percentile vs the median and the median vs the 10th percentile	Compnet
Mean wage percentile	10th, 25th, 50th, 75th, 90th, 95th, 99th percentile of labour cost per employee	Compnet
Labour markdown	Labour markdown estimated on a firm-level Cobb-Douglas production function according to Ackerberg–Caves–Frazer method (2015)	Compnet
Markup	Markup estimated on a firm-level Cobb-Douglas production function according to Ackerberg–Caves–Frazer method (2015)	Compnet
Labour market concentration	Hirschmann-Herfindal Index of employment shares across firms	Compnet
Tertiary education	Share of population 15 years or over with tertiary education (levels 5-8)	Eurostat
Foreign active population	Share of foreign active population over total foreign population	Eurostat
Female employment rate	Share of female active population over total female population	Eurostat
Elementary occupations	Share of employed workers in low-skilled occupations. Low-skilled occupations include non-qualified occupations, corresponding to the ISCO macro-group of elementary occupations (ISCO code 9)	Eurostat
Median age	Population median age	Eurostat
Metropolitan region	Dummy variable taking value 1 for regions with a share of regional population living in Eurostat-defined metropolitan areas above the 90th percentile value and 0 otherwise	Eurostat
Trade exposure	Regional capacity for internationalization	ESPON
Robot density	Three-years average of robot stock per 1,000 employees in manufacturing	International Robot Federation (IFR) and Eurostat SBS

Note: dependent variables available in the years 2009-2020; independent variables available in the years 2008-2019, except the automation variable available in the period 2011-2019.
Source: Authors' construction

Table A2: Summary statistics/ *Összegző statisztikák*

Variable	*Mean*	*Std.dev.*	*Min*	*Max*
Wage difference				
90^{th} to 10^{th}	28.59	14.51	5.80	81.71
90^{th} to 50^{th}	16.00	7.92	3.92	45.31
50^{th} to 10^{th}	12.60	7.34	1.86	38.50
Wage ratio				
90^{th} to 10^{th}	2.77	0.74	1.79	5.51
90^{th} to 50^{th}	1.58	0.22	1.30	2.45
50^{th} to 10^{th}	1.74	0.33	1.34	3.32
Mean wage percentile				
10^{th}	17.745	9.110	4.981	37.585
25^{th}	23.211	11.797	5.593	47.807
50^{th}	30.338	15.054	6.864	60.679
75^{th}	37.724	18.026	8.566	79.428
90^{th}	46.334	21.765	10.779	105.759
95^{th}	53.451	25.4265	12.729	136.198
99^{th}	74.370	38.279	22.317	227.017
Labour markdown	2.166	1.509	0.716	6.088
Tertiary education	24.21	8.70	8.44	45.44
Foreign active population	5.93	5.83	0.06	37.19
Female employment rate	45.79	2.74	36.72	50.95
Elementary occupations	9.21	3.91	0.00	26.82
Median age	43.48	2.75	35.80	51.00
Metropolitan region	15.44 (%)	36.25	0.00	1.00
Trade exposure	0.41	0.19	0.02	1.00
Robot density	0.0038	0.001	0.000	0.008
Markup	14.71	52.84	1.76	373.71

N = 149 x 8.
Source: Authors' construction