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The sources and structure of wage inequality changes in the selected Central-Eastern European Countries

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Abstract

We study the determinants of wage inequality and its fluctuations in six Central-Eastern European nations using European Union Statistics on Income and Living Conditions microdata from 2010 to 2019. Wage disparity in these countries changed in distinct ways. Inequality in Czechia and Romania is generally steady, has fallen consistently in Poland and Slovakia, and has increased in Bulgaria. Inequality has been steadily reducing in Hungary but has recently increased significantly. Therefore, this paper questions these countries' primary causes of wage inequality changes. In addition to providing a detailed description of inequality trends in these countries, we focus on examining the demographic and micro-level determinants alongside the minimum wage changes. We estimate these effects using RIF regression and RIF decompositions for various inequality measures. The changes in wage inequality in these countries were driven mainly by wage structure effects regardless of the increase or decrease in wage inequality. Changes in the returns to education and returns to permanent employment contracts are crucial in explaining decreased wage inequality. The increases in wage inequality in Hungary and Bulgaria are defined mainly by the changes in the estimated constants instead of micro-level determinants. The changes in the minimum wage explain most of the unknown factors in Bulgaria, and the spillover effects of the minimum wage may explain most of the unknown factors in Hungary. Our results can support the skill-biased technological change hypothesis in the case of Slovakia, Romania, Czechia, and Bulgaria.

Keywords Wage inequality · RIF regression · RIF decomposition · Oaxaca-Blinder decomposition · Central-Eastern Europe · EU-SILC

JEL Classification J31 · D30 · D31 · D22 · C46

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1 Introduction

Relatively high or rising wage inequality remains a significant social and economic difficulty today. The United Nations' Agenda 2030 for Sustainable Development of 2015 has declared a global vision of achieving full employment with an equal wage. Wages and salaries account for a notable portion of the income from employment, around 80% of the total earnings of employment (Katz & Autor 1999). Thus, widening wage inequality is harmful to socioeconomic well-being through many channels. Wage disparities lead to household income and consumption inequality, implying a noticeable change in differences in economic well-being (Cutler & Katz 1992). Moreover, wage dispersion is the cause of many social issues, such as poverty, crime, unemployment, health problems, lower life expectancy, and limited access to education (Stiglitz 2012).

A substantial wage differential started in the 1980s and was maintained in the following decades in the US, which spread to other countries, including Canada, the UK, and some European countries. Much research documented the US's wage structure changes (Katz & Autor 1999; Autor et al. 2008). Income inequality rose sharply in Eastern Europe and Central Asia (EECA) during the transition periods (the 1990s), but the average inequality has gradually declined since then (Ravallion 2016). European Union Statistics on Income and Living Conditions (EU-SILC) presents a diverging trend in income inequality in EU countries. This research focuses on Central-Eastern Europe (CEE), particularly concerning six countries: Bulgaria, Romania, Poland, Hungary, Czechia, and Slovakia. These countries are geographically close and have experienced similar political and economic conditions during the 1970s and 1980s. Additionally, they have all undergone a transition from centrally planned economies to market-based systems. However, their subsequent development has diverged, making them valuable subjects for analysis. In these nations, income inequality has been widening (Bulgaria and Hungary), shrinking (Poland and Slovakia), and stable (Czechia and Romania) over the last decade.

It is intriguing to understand why income disparities differ between countries that began at a similar point in the transition. Pereira & Galego (2019) point out that it is complicated to comprehend the differing movements in wage disparity for European Union countries, which share a similar environment in terms of technological growth and globalization. It is unclear whether the primary explanations for changes in inequality proposed by the economic literature – skill-biased technological change (SBTC) and international trade and globalization hypotheses – explain the factors underlying the patterns of wage disparity in the selected countries. This is because both assumptions are attributed to an increase in the relative demand for skilled workers, which raises their relative wages and causes wage inequality. Distributional outcomes generally result from many economic, demographic, and structural forces, making it difficult to pinpoint the causes of inequality. In particular, transitional countries' structural and institutional changes have compounded this complexity. As a result, a more in-depth, analytical investigation is required to comprehend the changes in wage inequality in the selected CEE countries.

During the socialist period, CEE countries had relatively low levels of income inequality (Medgyesi & Tóth 2021). However, a transitional recession in the early 1990s led to a significant decrease in GDP and an increase in income inequality (Flemming & Micklewright 2000). Numerous studies examined inequality during this transition period, revealing that widening gaps in labor income distribution, the growing prominence of capital income, and the diminishing influence of welfare state programs were pivotal factors contributing to the escalating income inequality in CEE countries (Medgyesi & Tóth 2022). However, there were differences in policies and outcomes among the selected countries during the transition period. Czechia and Slovakia have shown resilience to inequality shocks due to efficient tax and social policies (Kahanec et al. 2014). Poland experienced a modest rise in inequality due to free-market principles and financial considerations (Letki et al. 2014). Bulgaria and Romania experienced two waves of inequality increase, while Hungary experienced a smaller increase due to earlier liberalization, strong inequality forces, and social policies protecting lower-end labor market workers (Tóth 2008; Tsanov et al. 2014; Precupetu & Precupetu 2014).

Some studies have extended their focus to encompass the periods of EU accession and the global financial crisis. Brzezinski (2018) found that during the financial crisis, income inequality increased in Bulgaria and Hungary, driven by factors such as Hungary's less progressive tax system and Bulgaria's decrease in full-time employment rate. However, the crisis did not significantly impact income inequalities in Romania, Poland, Czechia, and Slovakia. The existing body of literature indicates a gap, particularly in research addressing income inequality from the aftermath of the global financial crisis to the pre-COVID crisis. In response to this gap, this study focuses to the timeframe spanning from 2010 to 2019, aiming to shed light on the dynamics of income inequality during this period.

This research seeks to answer the following questions:

(i) How has wage inequality in these countries evolved over the last decade?
(ii) What are the micro-level determinants of wage inequality in these countries?
(iii) What are the effects of wage structure and composition on changes in wage inequality in these countries?

To that end, we first document and compare the evolution of wage distribution over the last decade for six nations, concentrating on four income inequality indicators, such as the Gini index and log wage gaps (90–10, 90–50, and 50–10). Second, we examine the leading sources of wage inequality in the six countries. We especially analyze which micro-level factors, such as individual, socioeconomic, and industrial factors, influence various measures of wage inequality in these nations. To do so, the recentered influence function (RIF) regression is used to estimate the impact of covariates on the Gini index and log wage disparities (90–10, 90–50, and 50–10) in each country. This approach allows us to understand better the influence of covariates on changes in various distributional statistics along the wage distribution.

Finally, the impact of covariates on changes in inequality measures from 2010 to 2019 is decomposed into two components: a wage structure effect and a composition effect. It enables us to know whether changes in wage inequality are caused by differences in covariates (composition effect), differences in the rewards of observed covariates (wage structure effect), or both. In this step, the RIF decomposition approach introduced by Firpo et al. (2018), an extension of the Oaxaca-Blinder (OB) decomposition on the distributional statistics other than the mean, is applied. In addition, the impact of minimum wage changes on the variation in wage inequality is investigated in this step. These empirical analyses are conducted based on Eurostat and European Union Statistics on Income and Living Conditions (EU-SILC) microdata from 2010 to 2019 for the six selected CEE countries.[1]

[1] The responsibility for all conclusions drawn from the data lies entirely with the authors.

This study contributes to literature on wage inequality in CEE countries through several avenues. Firstly, we underscore the importance of the study's coverage period and the diversity in inequality measurement. In bridging the identified research gap, our investigation delves into wage inequality in CEE countries from the aftermath of the global financial crisis to the pre-COVID period (2010–2019). Recognizing the limitations of the Gini index, a widely used metric, in capturing nuanced wage patterns, our study addresses this challenge by incorporating and comparing alternative inequality measures alongside the Gini index. These alternatives provide valuable insights by spotlighting specific points or regions within the wage distribution.

Secondly, our study augments the existing literature by exploring the impact of demographic and micro-level factors on wage inequality in CEE countries. This is noteworthy as specific demographic and micro-level factors, although utilized to explain wage disparity determinants, are seldom employed in CEE studies, making them insufficient for validating prior research findings. Our study, in particular, corroborates some of the findings identified by Magda et al. (2021), using different data and a distinct time frame. Moreover, it introduces new evidence on the factors contributing to both the reduction and increase in wage inequality.

Thirdly, our study differentiates between changes in inequality resulting from market forces (composition effect and/or structure effect) and changes caused by the minimum wage. Notably, despite covering different periods, our findings in Hungary exhibit some alignment with Pereira & Galego (2019). This alignment is valuable as it verifies prior results with more recent data, indicating that trends continue similarly.

The following is how the paper is structured. Section 2 reviews the literature focused on wage inequality in CEE countries. The methods employed in the empirical analysis are described in Section 3. Section 4 contains data and variables, and Section 5 explains the findings. Finally, it provides closing remarks.

2 Literature review

The significant shifts in the wage distribution of advanced countries have led to extensive literature on changes in wage inequality and its determinants. Some of this literature has investigated the macro-level determinants of wage disparity and how international trade (Autor et al. 2014; Helpman et al. 2017; Lundberg & Squire 2003; Ravallion 2018), labor market frictions (Krishna et al. 2012), skill-biased technological change (Acemoglu 2002; Acemoglu & Autor 2011; Card & DiNardo 2002; Katz and Murphy 1991; Lemieux 2008), migration (Borjas 2003; Yabuuchi & Chaudhuri 2007), and institutional changes such as de-unionization and minimum wage (Autor et al. 2016; Machin 2016) have contributed to wage inequality. Some studies have looked at the micro-level determinants of wage inequality and found that wage inequality varies depending on worker and firm characteristics, such as individual, occupational, and industry (Akerman et al. 2013; Fortin et al. 2012). Although these determinants may explain wage differences to some extent, no single factor can explain all or even most of the changes in the wage structure. Autor et al. (2008) explain much of the difference in wage inequalities by incorporating variations in the relative supply and demand for skilled employees and labor market institutional factors.

It is uncertain, however, if the explanations for wage inequality in advanced countries are also consistent with labor market trends in other countries. Few studies have specifically addressed recent changes in wage inequality in emerging economies, particularly in

CEE countries. The factors directly associated with structural and institutional transition played a crucial role in explaining the wage disparity at the beginning of the transition period (the 1990s) when income inequality expanded significantly in all those countries (Aristei & Perugini 2014; Milanovic & Ersado 2012). Looking at individual countries, tax and transfer played an essential role in overall inequality in Hungary (Kattuman & Redmond 2001), Czechia, and Slovakia (Garner & Terrell 1998), and increased wage gaps in the private and public sectors in Poland (Adamchik et al. 2003; Keane & Prasad 2006) and Romania (Skoufias 2003).

The next strand of literature has taken a partial approach to investigate the determinants of wage inequality by maintaining a cross-country perspective. On one hand, the role of education and technological change (Esposito & Stehrer 2009; Tyrowicz & Smyk 2019), individual and firm characteristics (Magda et al. 2021; Simón 2010), labor market institutional settings, such as temporary contracts (Rutkowski et al. 2005), dual labor market (Hölscher et al. 2011), the role of institutions (Perugini & Pompei 2017), and foreign direct investment Onaran & Stockhammer 2008) are considered in explaining wage inequalities in CEE countries when market-based economies became dominant. An educational upgrade, minimum wage, and foreign firms in the domestic market contribute to the within-country wage differentials. In contrast, firm and industry-related factors contribute to the between-country wage gaps.

On the other hand, Roser & Cuaresma (2016) conducted a full-fledged empirical investigation of the causes of income inequality, employing the most comprehensive panel dataset available for 32 OECD countries over four decades and a plethora of theoretically indicated variables. It takes a comprehensive approach to identify the causes of income disparities and employs imports from less developed, non-oil exporting nations as a measure of international trade. This study concluded that government size, the interaction of technology and education, democratization, and labor market reconfiguration by unions all contribute to the dynamics of income disparity in industrialized countries.

Furthermore, the recent study by Pereira & Galego (2019) examined the roles of individual and firm characteristics and the minimum wage in the diverging wage inequality for eight European countries, including Hungary and Poland. Workers' educational advancements were found to play a crucial role in rising wage inequality in the majority of countries. In contrast, minimum wage changes, the proportion of non-native employees, and native wage premiums contribute to increasing or decreasing wage inequality. In particular, changes in the minimum wage in Hungary and Poland explain much of the reduced wage disparities. They also found that the returns to seniority in Poland contributed to the reduced wage inequality. In contrast, in Hungary, the return to education, occupations, and the native wage premium all played a role.

Regarding the evolution of wage inequality, a few studies have directly addressed the recent wage inequality trends in these countries. Tyrowicz & Smyk (2019) documented that wage inequality was initially lower in transition nations but quickly surpassed levels reported in advanced economies when the economic system changed. This phase was followed by a gradual decrease in wage inequality due to immediate adjustments. Magda et al. (2021) showed that wage disparity declined in all but one of the nine CEE countries (the selected six countries in this study were included) between 2000 and 2010. The only country in CEE where wage inequality slightly rose during this period was Czechia, which nonetheless has the lowest levels of wage inequality in the area. Wage inequality decreased primarily in the lower tail of the wage distribution; however, the Baltic nations also observed a fall in wage dispersion in the upper tail. Furthermore, Vacas-Soriano et al. (2020) found that wage convergence was the primary factor influencing wage inequality trends across the EU between 2004 and 2015, as evidenced by the fact that wage disparities narrowed significantly before the crisis as a result of wage catch-up growth, particularly in Eastern Europe. The crisis temporarily halted this trend but has since been revived.

3 Empirical methodology

In this study, we employ an empirical strategy based on RIF regression and decomposition. Firpo et al. (2009) introduced recentered influence functions (RIFs) for estimating the partial effect of regressors on the unconditional quantiles of the outcome variable. Firpo et al. (2018) explore using RIF regressions for the variance of log wage and Gini index, focusing on the extension to the OB decomposition relying on RIFs. The strong point of RIF regression is its compatibility with any distributional statistics, such as mean, quantiles, and inequality measures (percentile differences and ratios, or the Gini index), and the potential extension of generalizing the classic OB decomposition for examining changes in outcome distributions across groups.

We first run RIF regressions for the log wage gaps (90–10, 90–50, and 50–10), and the Gini index to examine the evolution of wage inequality across the wage distribution. In the second stage, changes in these wage disparity measures are decomposed into composition and wage structure effects using the RIF decomposition approach developed by Firpo et al. (2018).

RIF regression Firpo et al. (2009) employ a method to compute unconditional partial effects of changes in the distribution of covariates on a given function of the *Y* distribution. The approach works by offering a linear approximation to a non-linear function of the distribution. Namely, their method relies on the influence function (IF), a statistical instrument for analyzing statistical robustness (Cowell & Flachaire 2015). In short, the influence function $IF\{y_i, v(F_Y)\}$ represents the impact of an individual observation y_i on a distributional statistic $v(F_Y)$. Firpo et al. (2009) offer a recentered version of the statistics by adding the statistic $v(F_Y)$ to the influence function instead of using IF directly.

$$RIF\{y_i, v(F_Y)\} = v(F_Y) + IF\{y_i, v(F_Y)\} \tag{1}$$

It can be interpreted as the relative contribution of observation y_i to the generation of the statistic v. A useful property of the RIF is that its expectation equals the distributional statistic itself $v(F_Y)$. Therefore, the advantage of using RIF is that it easily generalizes beyond quantiles to other options of v, such as the variance, the Gini coefficient, and other inequality measures. For the case of quantiles, the RIF is defined as $RIF\{y_i, v(F_Y)\} = q_Y(p) + [p - 1\{y \le q_Y(p)\}]/[\{fq_Y(p)\}]$, where $q_Y(p)$ is the p-th quantile of Y.

Following Firpo et al. (2009), the RIF regression is the conditional expectation of the $RIF\{y_i, v(F_Y)\}$ modeled as a distribution function of the explanatory variables:

$$E[RIF\{y_i, v(F_Y)\}|X = x] = m_v(X) \tag{2}$$

When used to quantiles, this is equivalent to unconditional quantile regression. The basic method for estimating RIF regression is to assume a linear relationship between $RIF\{y_i, v(F_Y)\}$ and covariates X.

$$RIF\left\{y_i, v\left(F_Y\right)\right\} = \mathrm{X}'\beta + \varepsilon_i,\ E\left(\varepsilon_i\right) = 0 \tag{3}$$

In this context, OLS can be used to estimate the effects of changes in the distribution of X on $v\left(F_Y\right)$. As shown in Eq. (3), $RIF\left\{y, v\left(F_Y\right)\right\}$ for each observation y_i is the dependent variable and we need to calculate it before conducting RIF-OLS regression. RIF computations differ according to the statistics. Some statistics, as the mean, are easily estimated, whereas others need numerous intermediate steps to appropriately define their corresponding RIFs. The new dependent variable is then regressed against the covariates.

The interpretation of RIF-OLS differs slightly from that of normal OLS in that the unconditional partial effects on the statistic v are considered. To do so, one must first obtain unconditional expectations on both sides of the Eq. (3).

$$v\left(F_Y\right) = \mathrm{E}\left[RIF\left\{y_i, v\left(F_Y\right)\right\}\right] = \mathrm{E}\left(\mathrm{X}'\beta\right) + \mathrm{E}\left(\varepsilon_i\right) = \overline{\mathrm{X}}'\beta \tag{4}$$

where, $\overline{\mathrm{X}}$ is the unconditional mean, $\overline{X}_1, \dots \overline{X}_k$. Thus, the unconditional partial effect is:

$$\frac{\partial v\left(F_Y\right)}{\partial \overline{\mathrm{X}}_k} = \beta_k \tag{5}$$

Therefore, the interpretation of the unconditional partial effect is defined as the amount by which the distributional statistic changes when the unconditional average of the distribution of x_k increases by one unit.

RIF decomposition The OB decomposition is a popular tool in labor economics that decomposes the differences in mean wages into a composition effect (differences in characteristics) and wage structure effect (differences in coefficients of these characteristics), but it cannot be applied to partition the composition effect into the contributions of individual covariates regardless of the decomposition order. Recently, Firpo et al. (2018) offered an extension to the OB decomposition as a method for decomposing differences in distributional statistics further than the mean by combining RIF regression with a reweighting strategy (DiNardo et al. 1996). This approach is known as RIF decomposition. Compared to previous approaches in the literature, this method has three benefits: (i) it is easy to apply, (ii) it allows for examining the role of each covariate on the aggregate decomposition, and (iii) it can be generalized to any distributional statistic that can be computed using RIF.

Assume the wage determination procedure is provided by:

$$Y_{t,i} = g_t\left(X_i, \varepsilon_i\right), t = 0, 1 \tag{6}$$

where X is the exogenous characteristics of workers, and ε_i is an unobserved component. We further suppose that the dependent variable Y, the exogenous characteristics X, and the categorical variable t have a joint distribution function that describes their interactions, which can be written as follows:

$$F_{Y|t=k} = \int F_{Y|X,t=k} dF_{X|t=k} \tag{7}$$

The cumulative conditional distribution of Y can be used to determine the change in the distributional statistic v from $t = 0$ to $t = 1$:

$$\begin{aligned}\Delta v = v_1 - v_0 = v\left(F_{Y|t=1}\right) - v\left(F_{Y|t=0}\right) = \\ = v\left(\int F_{Y|X,t=1} dF_{X|t=1}\right) - v\left(\int F_{Y|X,t=0} dF_{X|t=0}\right)\end{aligned} \tag{8}$$

It is clear from (8), that discrepancies in the distributional statistic (Δv) will result due to differences in the distribution of X ($dF_{X|t=1} - dF_{X|t=0} \neq 0$) or differences in the relationship between Y and X ($F_{Y|X,t=1} - F_{Y|X,t=0} \neq 0$). This is analogous to comparing differences in mean characteristics and differences in coefficients in the context of the conventional OB decomposition. To decompose the change in the distributional statistic (Δv) into composition effect (differences in the distribution of X) and wage structure effect (differences in coefficients), a counterfactual statistic (v_c) must be constructed, which is the distribution obtained by integrating the wage structure of $t = 0$ with the characteristics of $t = 1$.

$$v_c = v\left(F_Y^c\right) = v\left(\int F_{Y|X,t=0} dF_{X|t=1}\right) \tag{9}$$

The change in the distribution statistic v can be divided into two components using this counterfactual statistic:

$$\Delta v = \underbrace{(v_1 - v_c)}_{\substack{wage\ structure \\ effect\ (\Delta v_S)}} + \underbrace{(v_c - v_0)}_{\substack{composition \\ effect\ (\Delta v_X)}} \tag{10}$$

The first term, wage structure effect, refers to the changes explained by the changes attributed to the relationship between Y and X (rewards of observed characteristics) from $t = 0$ to $t = 1$ while holding the level of characteristics at $t = 1$ constant. The second term, composition effect, refers to the change caused by differences in the distribution of X from $t = 0$ to $t = 1$ while keeping the level of rewards at $t = 0$ constant.

However, identifying the counterfactual statistic v_c is challenging because the characteristics and outcomes implied by the counterfactual distribution ($F^c_{Y|X}$) cannot be explicitly observed. Two broad techniques for identifying the counterfactual statistic v_c have been proposed (Fortin et al. 2011). The first technique employs the conventional OB decomposition, identifying v_c using linear regressions and their approximations. However, Barsky et al. (2002) argue that in this situation, the counterfactual statistic v_c may be mistakenly detected if the model is incorrectly specified or distributional statistics are poorly estimated. They proposed an alternate technique for estimating the counterfactual distribution on the reweighted sample based on the reweighting approach developed by DiNardo et al. (1996). The technique is briefly described below.

The basic idea of Barsky et al. (2002) is that the counterfactual distribution can be approximated by multiplying the observed distribution of X ($dF_{X|t=0}$) by a factor $\psi(\mathrm{X})$, so that it matches the distribution $dF_{X|t=1}$.

$$F_Y^c = \int F_{Y|X,t=0} dF_{X|t=1} \cong F_{Y|X,t=0} dF_{X|t=0} \psi(\mathrm{X}) \tag{11}$$

where $\psi(\mathrm{X})$ is the reweighting factor:

$$\psi(\mathrm{X}) = \frac{dF_{X|t=1}}{dF_{X|t=0}} = \frac{dF_{t=1|\mathrm{X}} dF_X}{dF_{t=1}} \bullet \frac{dF_{t=0}}{dF_{t=0|\mathrm{X}} dF_X} = \frac{P(t=0)}{P(t=1)} \bullet \frac{P(t=1|\mathrm{X})}{1 - P(t=1|\mathrm{X})} \tag{12}$$

where $P(t = 1)$ *and* $P(t = 0)$ are the sample fractions for $t = 1$ *and* $t = 0$, respectively. $P(t = 1|\mathrm{X})$ is the conditional probability of a worker with characteristics X being in the sample at $t = 1$. In practice, this probability is computed using a probability model such as logit or probit (S. Firpo & Pinto 2016).

Following (4), separate RIF regressions for distributional and counterfactual statistics can be estimated as follows:

$$v_1 = \mathrm{E}\left[RIF\left\{y_i, v\left(F_{Y|t=1}\right)\right\}\right] = \overline{\mathrm{X}}^{1\prime}\hat{\beta}^1 \tag{13}$$

$$v_0 = \mathrm{E}\left[RIF\left\{y_i, v\left(F_{Y|t=0}\right)\right\}\right] = \overline{\mathrm{X}}^{0\prime}\hat{\beta}^0 \tag{14}$$

$$v_c = \mathrm{E}\left[RIF\left\{y_i, v\left(F_Y^c\right)\right\}\right] = \overline{\mathrm{X}}^{c\prime}\hat{\beta}^c \tag{15}$$

As a result, the decomposition components are now defined:

$$\Delta v = \underbrace{\bar{\mathrm{X}}^{1\prime}(\hat{\beta}^1 - \hat{\beta}^c)}_{\Delta v_s^p} + \underbrace{(\bar{\mathrm{X}}^1 - \bar{X}^c)'\hat{\beta}^c}_{\Delta v_s^e} + \underbrace{(\bar{\mathrm{X}}^c - \bar{X}^0)'\hat{\beta}^0}_{\Delta v_X^p} + \underbrace{\bar{\mathrm{X}}^{c\prime}(\hat{\beta}^c - \hat{\beta}^0)}_{\Delta v_X^e} \tag{16}$$

$\Delta v_s^p + \Delta v_s^e$ is the aggregate wage structure effect, where Δv_s^p is pure wage structure effect, and Δv_s^e is the reweighting error. The reweighting error, which is supposed to be zero in large samples, is used to assess the quality of the reweighting approach. A substantial and statistically significant reweighting error may suggest that the counterfactual was poorly recognized, in this case the probit or logit model specification used to estimate reweighting factors may need to be revised. $\Delta v_X^p + \Delta v_X^e$ is the aggregate composition effect, where Δv_X^p is pure composition effect, and Δv_s^e is the specification error. The accuracy of the model specification and the RIF approximation can be evaluated using the specification error. A substantial and statistically significant specification error may suggest that the RIF regression was misspecified or that the RIF's approximation of the distributional statistic was poor (Rios-Avila 2020).

However, it is essential to highlight that the main limitation of OB decompositions—the "omitted group" problem— persists in this extension. When dealing with categorical covariates, the impact of each covariate on the wage structure effect is contingent upon the selection of the reference group. Indeed, the issue of interpretation can emerge for any covariate, whether continuous or categorical, when there is no distinctly interpretable baseline value. Unfortunately, there is no straightforward solution to address this inherent challenge. Fortin et al. (2011) contend that proposing a generic solution to the omitted group problem is misguided, instead emphasizing the significance of utilizing economic reasoning to propose counterfactual exercises and recommending easy procedures for computing these exercises for distributional statistics. To address the omitted group problem, this study carefully chooses reference groups in decomposition analysis with a meaningful economic interpretation or lower sensitivity to estimates, achieved through multiple experimental estimations.

4 Data and variables

The empirical analysis is conducted using EU-SILC microdata[2] from 2010 to 2019 for the six CEE countries. EU-SILC is an annual Eurostat survey with a standard questionnaire that provides comparative microdata on income, poverty, social exclusion, living conditions, and labor market activities for EU countries. Data on social exclusion and housing circumstances are mostly gathered at the household level, whereas income, labor, education, and health data are gathered from individuals aged 16 and up. This study uses individual-level data. Employees aged 18 to 64 with non-zero employee income in the reference year are included in the sample. Unpaid family workers and the self-employed are excluded. In the case of the self-employed, challenges related to defining and accurately measuring self-employment income not only introduce inaccuracies in income data but also create a lack of comparability across time and different countries. The presence of numerous outliers, missing values in self-employment income, and significant variation in self-employment rates across countries are the reasons for excluding self-employed individuals from the sample. Additionally, self-employment income sources pose reliability problems in EU-SILC compared to national accounts (Eurostat 2020).

As a result, 404,951 employees are included in calculating inequality trends between 2010 and 2019 and the estimation of the RIF regression, with a minimum sample size of 50,283 (Romania) and a maximum of 100,612 (Poland) at the country level (Table 8 in the Appendix). The sample size for wage inequality decomposition for the selected countries is 84,158 (43,899 in 2010 and 41,259 in 2019), which is 20.8% of the full sample because two time periods, 2010 and 2019, are considered, and individuals who lack information on any of the explanatory variables are also excluded.

The hourly wages are used to determine inequality measures (see Table 1 for further details). It is worth noting that among the income variables in the EU-SILC, no specific variable solely defines wages, and incomes are collected by the income reference period[3] (Wirth & Pforr 2022). This poses a challenge and limitation in accurately defining the outcome variable as a wage. Although information on employee gross monthly earnings is available in the EU-SILC dataset, it is restricted to only a limited group of countries, with only two selected countries included. Consequently, we utilized the gross employee cash or near-cash income variable as a proxy for wages since it is defined as the monetary component of total remuneration payable by an employer to an employee during the income reference period. However, it is important to note that treating it as wage can have a limitation. As it includes wages and salaries paid for time worked or work done, it may reflect a person's dependent labor, involving different jobs with varying wages throughout the income reference period.

Figure 1 shows the evolution of mean real hourly wages (on a logarithmic scale) from 2010 to 2019. Each country's average hourly wage has consistently increased over time. Among the selected countries, Czechia had the highest average hourly wage between 2010 and 2019, while Bulgaria and Romania had the lowest. Bulgaria's average hourly wage was 56 percent of Czechia's average as of 2019. In Fig. 6 in the Appendix, the hourly wage distributions in 2010

[2] EU-SILC reference population consists of all private households and current members resident in the territory of the Member States (MS) at the time of data collection (Commission Regulation (EC) No 1982/2003). The minimum effective sample size to be attained in terms of precision criteria for the most critical variables and the aims of providing results both at the individual nation level and at the EU level as a whole (Regulation (EC) No 1177/2003).

[3] The income reference period is "Months with any work" (Eurostat 2020).

Table 1 Description of variables

Name of variable	Description
Hourly wage	Inequality measures employed as dependent variables are derived from the logarithm of hourly wage. The gross employee cash or near-cash income variable is used as a proxy for wages. It pertains to the monetary component of employee compensation in cash, which an employer pays an employee during the income reference period before any deductions for taxes and social insurance contributions (Eurostat 2020). These wages were then divided by the hours worked for each employee. According to Eurostat (2020), gross employee cash or near cash income includes not only their base salaries and wages but also other forms of compensation such as overtime pay, commissions, tips, gratuities, supplemental payments (thirteenth-month payment, and holiday payments), profit shares, and bonuses, additional payments based on productivity, allowances paid for working in remote locations, and transportation allowances. Hourly wages are measured in euros for all countries, and Eurostat converts the country's currency into euros using the average exchange rate based on the year before the survey (Eurostat 2020). The observations from the lowest and highest 0.05th percentiles of the hourly wage distribution were removed to reduce the potential effects of extreme values. The real hourly wages are calculated using the price deflator final private consumption in the European Commission's AMECO database[a]
Female	A dummy variable that equals one if an individual is female
Married	A dummy variable that equals one if an individual is married
Health difficulty	A dummy variable that equals one if the respondent reported feeling (strongly) limited in their typical activities for at least the past six months due to health difficulties
Education level	The highest level of education is measured using three dummy variables: lower secondary and below (ISCED[b] levels 0–2); upper secondary and post-secondary, non-tertiary (ISCED levels 3 and 4); and tertiary education (ISCED levels 5 and 6). The reference category is lower secondary and below
Experience	Years since completing the highest level of education in the survey year: year of the survey—the year in which the highest level of education was obtained. Due to this variable, we do not include age in our models, as the two are highly correlated
Permanent contract	A dummy variable that equals one if the respondent has a permanent job contract
Supervisory	A dummy variable that equals one if the respondent has supervisory responsibility
European Socio-Economic Groups (ESeG)	ESeG enables the identification of persons with similar economic, social, and cultural characteristics across the EU. ESeG is developed based on two main variables: occupation categorization (ISCO 2008, 1 and 2 digits) and employment status (employee or self-employed). It has nine groups, of which six groups are used in this study—expressed as dummy variables: (1) managers; (2) professionals; (3) technicians and associate professionals; (4) clerks and skilled service employees; and (5) skilled industrial employees; (6) less skilled employees. The reference category is less skilled employees

Table 1 (continued)

Name of variable	Description
The sector of economic activity	Industry dummies are generated based on a one-digit level of aggregation identifying the classification of economic activities (NACE Rev. 2 by Eurostat (2008)), which are: (1) agriculture (sections A); (2) industry (sections B-E); (3) construction (F); (4) trade (G); (5) low-skilled service sector (H, I, R-U); (6) high-skilled service sector (J-N); and (7) public service (O-Q). The reference category is the trade sector
Minimum wage	National gross monthly minimum wages are used from the Eurostat website, which references the values on the 1st of July of each year. To account for factors such as overtime pay and additional bonuses included in the wage measurement, the legal hourly minimum wages were adjusted upward by 5%. This adjustment aligned them with Eurostat's methodology for analyzing monthly minimum wages. Therefore, the equivalent hourly minimum wage is calculated by dividing the monthly minimum wage by the average monthly working hours (160 h) and multiplying the result by 1.05. The real minimum wages are calculated using the price deflator final private consumption in the European Commission's AMECO database

[a]Source: (https://economy-finance.ec.europa.eu/economic-research-and-databases/economic-databases/ameco-database_en)

[b]International Standard Classification of Education

and 2019 for the selected countries are compared, revealing a notable rightward shift indicating a significant increase in hourly wages across all countries, particularly Romania. Additionally, the dispersion of distributions has expanded, particularly in Bulgaria and Hungary, suggesting an increase in wage disparities within these countries. As a result, the positive average growth rate over the last decade does not imply that all residents' wages have risen. Specifically, it does not imply that the wage of individuals in the lower parts of the wage distribution have increased or that the number of people living below a given poverty line has dropped.

As explanatory variables for explaining wage inequality, we employ a large set of comparable demographic and micro-level characteristics across the six countries.

Table 1 describes all variables, while Table 9 in the Appendix displays the sample means of the explanatory variables employed in the analysis for 2010 and 2019. Poland has the highest proportion of people with higher education and workers in leading occupations such as managers and professionals as of 2019. Czechia and Slovakia have the highest share of employees with upper secondary and post-secondary education and those in middle occupations (particularly for technicians, associate professionals, clerks, and skilled service employees). Hungary and Bulgaria have the highest share of low-educated and less-skilled industrial workers (Table 9).

Monthly minimum wages vary among nations as of 2019, ranging from €286 in Bulgaria to €529 in Poland. The minimum wage has climbed significantly in all nations since 2010, with Romania having the greatest average annual growth rate between 2010 and 2019 (11.2%), followed by Bulgaria (8.9%). Czechia has the lowest average annual growth rate (4.2%), followed by Hungary (4.3%) (Fig. 2).

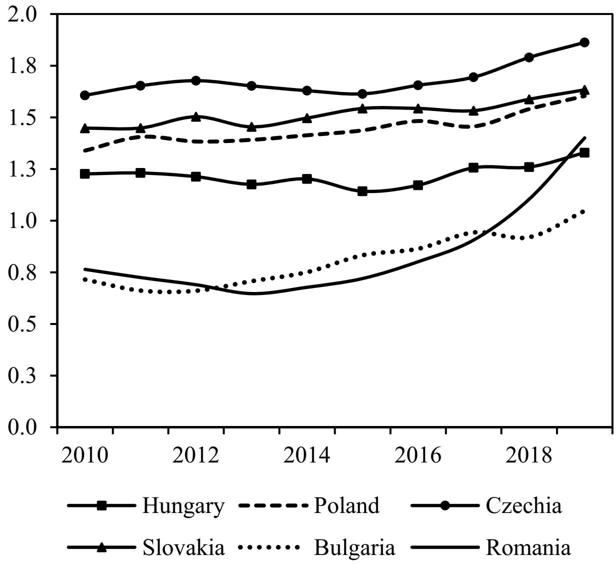

Fig. 1 The dynamic of mean log real hourly wages from 2010 to 2019. *Source*: Authors' calculation based on EU-SILC (Eurostat) data

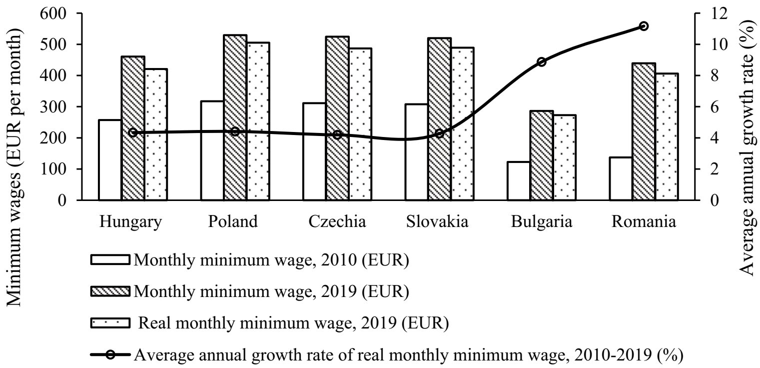

Fig. 2 Monthly minimum wages, 2010 and 2019. *Sources*: The source of monthly minimum wages is Eurostat (online data code: earn_mw_cur), and the source of the price deflator is the European Commission's AMECO database, accessed on November 6, 2023. Note: The base year for determining the real minimum wage was 2015

Table 2 presents the equivalent hourly minimum wage-related statistics in 2010 and 2019. In 2010, the ratio of minimum to average wages in all countries was less than 51%, but by 2019, this situation had altered dramatically, ranging from 45% in Czechia to 66% in Hungary. The equivalent hourly minimum wages in two countries, Hungary (66%) and Romania (60%), exceeded 60% of the mean hourly wages. This difference can be attributed to Hungary's relatively slower average wage growth, coupled with the more rapid increase in minimum wages in Romania. In 2019, the proportion of workers' hourly wages less than or equal

Table 2 Some statistics of equivalent hourly minimum wages

Country	Equivalent hourly minimum wages as a proportion of mean hourly wages (%)		The proportion of workers' hourly wages less than or equal to the equivalent hourly minimum wage in the sample (%)		Equivalent hourly minimum wage (EUR)		Hourly wages (EUR) 2010		Hourly wages (EUR) 2019	
	2010	2019	2010	2019	2010	2019	P10	P50	P10	P50
Hungary	48	66	12	25	1.7	3.0	1.6	2.9	1.4	4.1
Poland	51	59	19	22	2.1	3.5	1.7	3.3	2.9	4.9
Czechia	40	45	3	5	2.0	3.4	2.7	4.6	4.0	7.0
Slovakia	48	59	6	9	2.0	3.4	2.3	3.9	3.5	5.4
Bulgaria	40	55	7	27	0.8	1.9	0.9	1.7	1.4	2.7
Romania	47	60	8	19	0.9	2.9	1.0	1.6	2.7	4.1

Source: Authors' calculation based on the EU-SILC (Eurostat) data

to the equivalent hourly minimum wage ranged from 5% in Czechia to 27% in Romania. Generally, minimum wages are typically established at or below the 10th percentile of the wage distribution (DiNardo et al. 1996). However, Hungary, Poland, Bulgaria, and Romania differ from this norm, as their minimum wage levels surpass the 10th percentile.

5 Results

5.1 Trends in wage inequality

This section documents the changes in wage distribution observed in the selected countries between 2010 and 2019. Figure 3 begins by giving out basic wage structure facts to highlight wage inequality changes in the selected six countries over the last ten years. This graph depicts log real hourly wages change by percentile for each country from 2010 to 2019. It indicates a considerable growth in hourly wage at each percentile for all countries (except 1st, 10th, and 99th percentile earners in Hungary). Romania has made significant gains over other countries until the 90th percentile in the wage distribution, whereas Bulgaria has made the most significant gains at the 99th percentile. In contrast, Hungary and Slovakia have made minor progress relative to other nations in wage distribution over the last ten years.

Real hourly wage growth in Czechia and Romania is evenly distributed throughout all wage percentiles, especially between the 10th and 90th percentiles. Real hourly wage growth gradually drops throughout the wage distribution in Poland and Slovakia as the percentile in the wage distribution rises. It demonstrates that between 2010 and 2019, average hourly wage growth for low-income earners outpaced that of higher-income earners, indicating that wage gaps in these countries are shrinking. This pattern, however, differs in Bulgaria and Hungary. The wage discrepancy in Bulgaria has increased significantly, with the 90th percentile earners increasing by roughly 20 log points relative to the 10th percentile earners. In Hungary, persons around the middle of the wage distribution gained more than those at the bottom and top (Fig. 3).

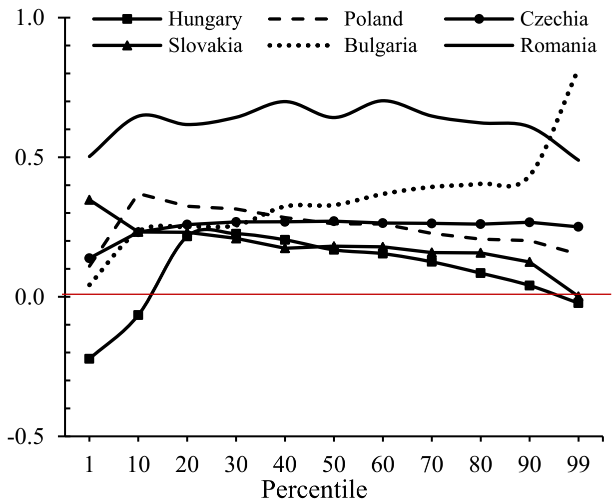

Fig. 3 Change in log real hourly wages by percentile, 2010 and 2019. Source: Authors' calculation based on EU-SILC (Eurostat) data

According to the Gini index of hourly wage, the countries were ranked in descending order of wage inequality in 2010: Poland, Hungary, Bulgaria, Romania, Czechia, and Slovakia (Fig. 4). Inequality evolved differently in these nations between 2010 and 2019. Specifically, Czechia and Romania's Gini index remained relatively stable throughout this decade. Poland and Slovakia, on the other hand, witnessed a consistent and gradual decline in the Gini index, albeit with some recent fluctuations in Slovakia. Hungary, initially showing a steady decline in the Gini index until 2017, has seen continuous increases over the past two years. In Bulgaria, the Gini index remained stable from 2010 to 2013, but there has been a substantial upswing in recent years (Fig. 4). Most of the rise is attributable to the widening wage inequality in the lower half of the wage distribution. This is evident in both nations, where average wage growth for people at the bottom of the wage distribution has been very low or negative (Fig. 3).

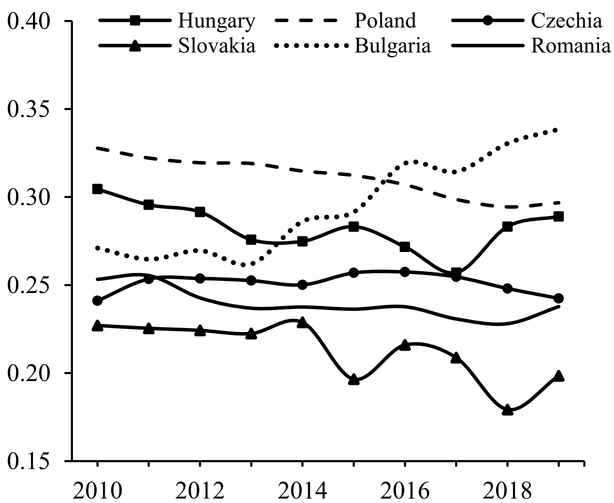

Fig. 4 Gini index of hourly wage, 2010–2019. Source: Authors' calculation based on EU-SILC (Eurostat) data

As a result of these dynamic changes in inequality, wage disparities in the selected nations diverged dramatically in 2019 compared to 2010 – particularly since 2013. Slovakia had the lowest Gini index of 0.23 in 2010, while Poland had the highest Gini index of 0.33. Slovakia still had the lowest Gini index in 2019, which fell to 0.20, while Bulgaria had the highest, at 0.34. The countries' ranks were changed in 2019 as follows (in descending order): Bulgaria, Poland, Hungary, Czechia, Romania, and Slovakia. Bulgaria's rise from third rank in 2010 to first place in 2019 was the most significant leap.

We also concentrate on three inequality measures: the 90–10 log wage differential summarizes changes in overall wage inequality; the 90–50 and 50–10 log wage differentials summarize changes in inequality in the top and bottom halves of the wage distribution. We commonly refer to these dimensions as upper-tail and lower-tail inequality, respectively. Figure 5 compares the evolution of each country's 90–10, 90–50, and 50–10 log wage gaps. Wage disparity at the upper tail of the distribution remained relatively steady across all nations from 2010 to 2019. Lower-tail wage inequality gradually declined in Poland and Slovakia, while it remained stable in Czechia and Romania. In contrast, wage inequality at the lower end experienced fluctuations in Hungary and Bulgaria. Thus, the divergent evolution of overall inequality of the selected countries reflects a secular fall or rapid rise in lower-tail inequality accompanied by a halt in upper-tail inequality expansion.

Table 3 presents between-group wage structure changes from 2010 to 2019 by subperiod for groups defined by gender, education, European socio-economic groups (ESeG), and sector. The first row indicates that the mean real hourly wage grew from 10.3 (Hungary) to 63.7 (Romania) log points over the full period. Wage growth slowed or declined in the five years (2010–2014) following the Great Recession but accelerated in 2015–2019. From 2010 to 2019, men experienced a slight wage increase relative to women in Hungary, Poland, and Czechia, while women gained slightly more than men in Slovakia, Bulgaria, and Romania. As a result, the gender wage gap in Slovakia, Bulgaria, and Romania narrowed by 2019, but the remaining three nations saw little increase (Fig. 7 in the Appendix).

The expansion of educational wage disparity is significant in the selected countries. Wages increased at all levels of education between 2010 and 2019 (except for Hungary's tertiary education); however, this differed by country. In Poland, Czechia, and Slovakia, individuals with lower levels of education experienced the most substantial wage growth. Conversely, those with middle-level education witnessed the highest wage increase in Hungary, Bulgaria, and Romania (Table 3). Consequently, by 2019, the wage gap related to educational levels had significantly decreased in Poland, Czechia, and Slovakia, while it had notably widened in Bulgaria (Fig. 8 in the Appendix).

All countries experienced notable shifts in wage differentials among socioeconomic groups (ESeG) between 2010 and 2019. However, the magnitude of these changes varied across nations. As indicated in Table 3, the mean hourly wages for low-skilled workers demonstrated a more rapid increase compared to other groups between 2010 and 2019 in Poland and Slovakia, whereas the mean hourly wages for managers and professionals experienced the least growth. In Hungary, however, mean log hourly wages for managers and professionals experienced a decrease. Consequently, wage disparities between socioeconomic groups and low-skilled workers have diminished in Poland, Slovakia, and Hungary (except for Industrial skilled employees) (Fig. 9 in the Appendix).

In contrast, in Czechia and Bulgaria, wage disparities between socioeconomic groups and low-skilled workers widened (Fig. 9 in the Appendix). Compared to other groups, this expansion is linked to increases in mean hourly wages within highly skilled groups, such as managers and professionals (Table 3). The hourly wage growth between 2010 and 2019 in Romania exhibited a generally similar trend across socioeconomic groups. However, the

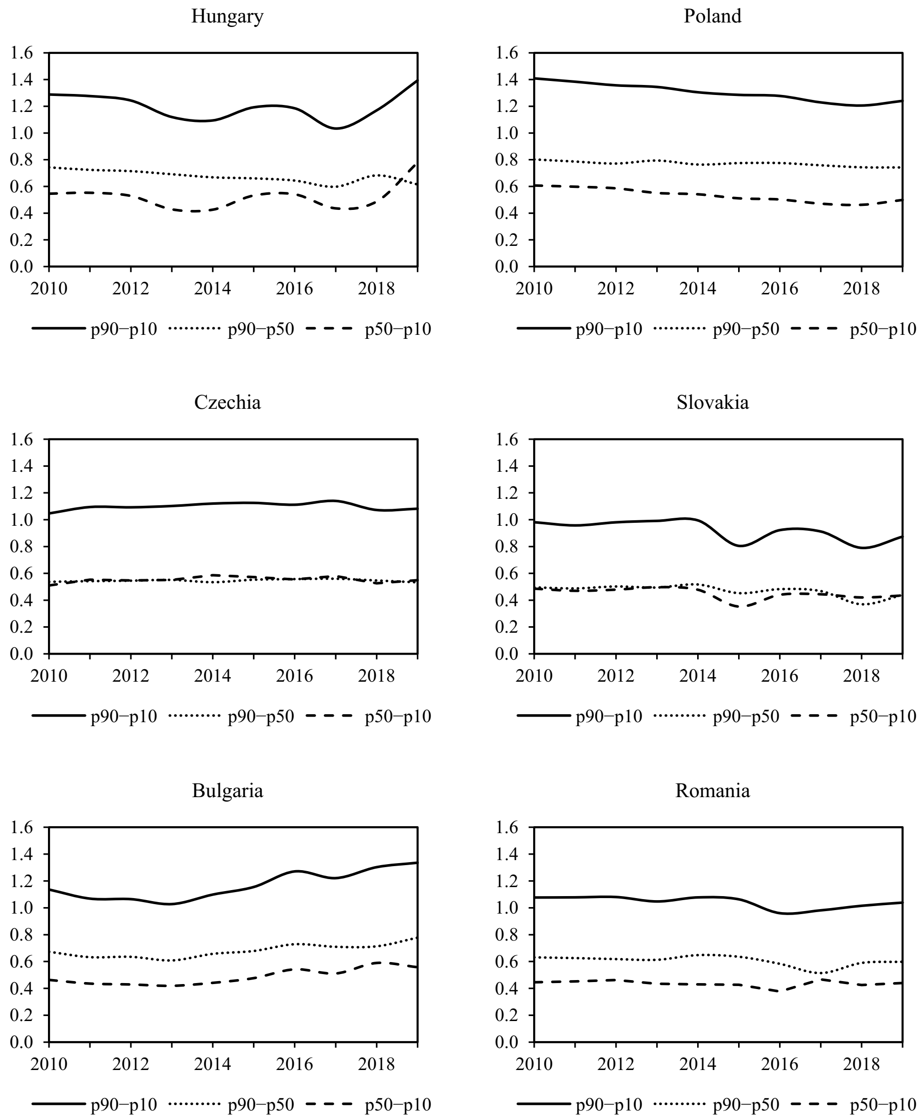

Fig. 5 Measures of wage inequality: 90–10, 90–50 and 50–10 log hourly wage gaps, 2010–2019. *Source:* Authors' calculation based on EU-SILC (Eurostat) data. *Note:* The overall 90–10 inequality series represents the difference in log hourly wages between the 90th and 10th percentiles. The 90–50 (upper-tail) series displays the difference in log hourly wages between the 90th and 50th percentiles. The 50–10 (lower-tail) series displays the difference in log hourly wages between the 50th and 10th percentiles

increase in mean hourly wages within low-skilled and middle-skilled groups was slightly higher than in highly-skilled groups (Table 3). Consequently, wage differentials between high-skilled groups (managers and professionals) and low-skilled workers decreased. Conversely, wage disparities increased between middle-skilled groups (technicians and associated professionals, clerks, skilled service employees, and industrial skilled employees) and low-skilled workers (Fig. 9 in the Appendix).

Table 3 Changes in log real hourly wages, 2010–2019 (100 × change in mean log real hourly wages)

Variables	Hungary			Poland			Czechia			Slovakia			Bulgaria			Romania		
	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019
All	-2.4	18.7	10.3	7.4	16.6	26.4	2.3	24.9	25.6	4.9	9.0	18.5	3.6	21.5	33.3	-8.7	68.1	63.7
Gender																		
Men	-1.5	20.7	12.5	8.0	16.6	28.3	3.3	25.7	27.5	5.1	9.9	18.3	6.3	18.0	32.5	-7.1	65.4	62.8
Women	-3.4	16.1	7.4	6.9	16.7	24.6	1.6	24.7	25.0	4.9	8.6	19.3	1.4	25.1	34.6	-10.4	71.6	65.1
Education																		
Lower secondary and below	0.1	28.5	15.4	7.0	20.5	31.8	0.2	27.5	24.6	8.2	7.6	23.8	-1.3	13.3	21.7	-10.0	49.6	60.2
Upper secondary and post-secondary, non-tertiary	-0.4	24.0	19.3	6.9	16.3	25.9	0.3	24.3	22.5	4.5	9.4	19.5	3.1	20.4	30.8	-8.9	67.1	62.5
Tertiary education	-9.1	6.5	-5.1	1.2	12.1	14.5	-1.7	22.2	19.7	1.6	9.6	13.4	5.6	25.1	41.4	-13.2	70.0	60.6
European Socio-Economic Groups																		
Managers	-3.5	1.8	-5.8	5.8	8.5	17.5	4.1	28.1	29.2	9.3	-1.5	7.1	14.6	21.2	44.4	-14.1	61.6	53.4
Professionals	-6.4	4.4	-2.7	0.5	11.3	12.2	-1.3	19.2	16.1	3.9	6.1	12.5	-3.1	30.6	40.5	-15.3	69.9	58.7
Technicians and associated professionals	-5.3	15.1	3.5	7.4	14.9	24.3	5.2	25.2	28.1	7.5	5.5	18.0	20.5	19.5	46.5	-5.5	68.7	67.0
Clerks and skilled service employees	-7.4	15.3	5.5	5.5	17.7	24.4	2.8	22.4	24.0	9.1	11.1	21.6	-2.2	25.8	29.5	-12.4	76.1	66.7
Industrial skilled employees	6.0	26.7	26.9	8.6	18.1	29.0	1.0	25.2	24.5	3.8	10.2	18.8	6.2	18.4	31.1	-5.7	64.6	65.6
Less skilled employees	-4.8	23.2	10.6	9.2	18.6	32.0	-4.5	28.9	22.1	10.3	12.9	30.8	1.3	17.3	27.5	-9.4	68.0	63.4
Sector																		
Agriculture	4.6	30.9	23.0	19.2	10.2	38.6	3.4	24.5	24.2	8.2	6.2	23.5	10.4	16.5	34.7	-5.8	69.2	69.9

Table 3 (continued)

Variables	Hungary			Poland			Czechia			Slovakia			Bulgaria			Romania		
	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019	2010–2014	2015–2019	2010–2019
Industry	1.7	23.9	21.4	8.5	16.9	28.6	2.2	25.6	26.3	3.4	7.4	13.8	2.9	25.1	33.2	-5.9	62.2	61.5
Construction	8.4	22.6	23.6	13.6	20.8	36.3	6.9	27.4	32.4	4.7	11.8	19.2	3.7	9.2	24.6	-8.6	67.6	60.9
Trade	-0.7	21.7	18.3	6.5	22.1	29.1	2.0	29.2	28.9	4.1	12.0	24.0	6.9	16.7	33.3	-10.1	66.4	61.2
Low-skill service	1.8	17.4	14.3	10.3	21.4	34.0	1.9	21.6	22.8	5.6	11.0	22.1	4.7	14.5	28.2	-6.8	65.9	65.2
High-skill service	-9.5	15.8	-2.0	5.8	17.1	26.2	8.3	19.7	26.0	10.7	7.0	23.0	7.6	22.4	37.6	-6.7	72.2	60.7
Public service	-11.5	10.0	-8.3	2.1	9.7	12.5	-2.8	25.8	21.0	4.6	8.5	17.7	-0.2	28.8	38.5	-12.5	82.0	75.2

Source: Author's calculation based on EU-SILC (Eurostat) data

All countries underwent significant changes in wage differentials among sectors between 2010 and 2019. Specifically, the mean hourly wages in the agricultural sector exhibited a more rapid growth in Poland, Hungary, Slovakia, and Romania compared to other sectors (Table 3). Consequently, the wage disparities between the agricultural sector and other sectors have decreased in these countries (Fig. 10 in the Appendix). Furthermore, mean hourly wages in the construction sector saw the highest increase in Hungary and Poland, while wages in the trade sector experienced the most significant growth in Czechia and Slovakia. Public service wages, on the other hand, saw the most substantial increase in Bulgaria and Romania (Table 3). As a result, the sectoral wage differences have narrowed in various industries in Hungary, Poland, Czechia, Slovakia, and Bulgaria compared to the trade sector; however, they have expanded in most sectors in Romania (Fig. 10 in the Appendix).

5.2 RIF regressions

This section examines the micro-level factors of wage inequality, estimated by RIF regressions for various log wage gaps (90–10, 90–50, and 50–10) and the Gini index. Table 4 reports the result of RIF regression for each country for these selected distributional statistics in a full sample from 2010 to 2019, together with robust standard errors. The average RIF is presented at the bottom of the table as a reference point for interpreting unconditional partial effects. Detailed marginal effects for the quantiles from the 10th to the 90th are provided in Fig. 11 for demographic and human capital variables, Fig. 12 for socioeconomic groups, and Fig. 13 for the sectors in the Appendix.

5.2.1 Demographic and human capital variables

Female gender and permanent contracts are the covariates that contribute to reducing wage inequality in the selected countries Although women's wages in all quantiles are consistently lower than men's across all selected countries, the female gender pay gap is more pronounced in Czechia and Slovakia. But wage gaps across the wage distribution in these two countries are smaller as female wage slopes are flatter (also in Romania). On the other hand, in Hungary, Poland, and Bulgaria, gender pay gap increases as one moves up the quantiles, indicating that the disparity between men and women is most pronounced at higher wage levels and narrower at lower levels (Fig. 11 in the Appendix). These findings suggest that enhancing women's participation in the workforce contributes to a decrease in all measures of wage inequality. Specifically, its impact is more pronounced in the lower tail than the higher tail of the wage distribution (Table 4).

Interpreting categorical variables in the context of unconditional partial effect is challenging. While coefficients of categorical variables should not be viewed as shifts from 0 to 1 due to potential bias, analyzing unconditional partial effect as deviations from observed unconditional averages is recommended based on Eqs. (4) and (5). Precisely, a one-percentage-point increase in the proportion of women in the workforce would lead to a predicted reduction of the Gini index by 14%[4] in Hungary, 10% in Bulgaria, 7% in Poland, 5% in Czechia, and 4% in Slovakia. However, the effect is not statistically significant for Romania.

[4] For example, estimated coefficient ×100/Avg.RIF = -0.04×100/0.288.

Table 4 RIF regression of wage inequality measures, full sample (2010–2019)

Variables	Hungary				Poland				Czechia			
	90–10	90–50	50–10	Gini	90–10	90–50	50–10	Gini	90–10	90–50	50–10	Gini
Female	–0.227***	–0.097***	–0.13***	–0.04***	–0.162***	–0.048***	–0.114***	–0.022***	–0.065***	–0.03***	–0.035***	–0.013***
	(0.01)	(0.008)	(0.007)	(0.003)	(0.009)	(0.008)	(0.006)	(0.002)	(0.009)	(0.007)	(0.007)	(0.002)
Married	0.048***	0.046***	0.001	0.01***	–0.005	–0.041***	0.036***	–0.011***	0.066***	0.019***	0.046***	0.011***
	(0.009)	(0.008)	(0.006)	(0.003)	(0.009)	(0.008)	(0.006)	(0.002)	(0.009)	(0.007)	(0.006)	(0.002)
Education ("Lower secondary and below" omitted)												
Upper secondary education	–0.227***	–0.11***	–0.117***	–0.036***	–0.107***	–0.098***	–0.009	–0.026***	–0.256***	–0.141***	–0.114***	–0.052***
	(0.013)	(0.008)	(.012)	(0.003)	(0.016)	(0.01)	(0.014)	(0.003)	(0.022)	(0.009)	(0.021)	(0.003)
Tertiary education	0.267***	0.173***	0.094***	0.062***	0.277***	0.169***	0.108***	0.048***	0.107***	0.051***	0.055**	0.018***
	(0.021)	(0.017)	(0.015)	(0.006)	(0.021)	(0.016)	(0.016)	(0.004)	(0.026)	(0.016)	(0.022)	(0.005)
Health difficulty	0.085***	0.054***	0.031***	0.024***	0.011	0.014	–0.003	0.003	0.205***	0.064***	0.140***	0.041***
	(0.013)	(0.01)	(0.01)	(0.005)	(0.013)	(0.011)	(0.009)	(0.003)	(0.016)	(0.010)	(0.014)	(0.003)
Experience	0.021***	0.009***	0.012***	0.004***	0.022***	0.015***	0.007***	0.005***	0.016***	0.005***	0.011***	0.004***
	(0.001)	(0.001)	(0.001)	(0.0001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.001)	(0.001)	(0.001)	(0.0001)
Experience^2	–0.044***	–0.02***	–0.024***	–0.009***	–0.045***	–0.03***	–0.015***	–0.009***	–0.030***	–0.011***	–0.018***	–0.007***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
Permanent contract	–0.521***	–0.153***	–0.368***	–0.082***	–0.139***	–0.095***	–0.044***	–0.039***	–0.232***	–0.104***	–0.129***	–0.046***
	(0.014)	(0.009)	(0.011)	(0.004)	(0.009)	(0.007)	(0.007)	(0.002)	(0.014)	(0.009)	(0.012)	(0.003)
Supervisory	0.296***	0.214***	0.081***	0.072***	0.204***	0.127***	0.077***	0.040***	0.191***	0.125***	0.066***	0.044***
	(0.018)	(0.017)	(0.008)	(0.006)	–0.107***	–0.098***	–0.009	–0.026***	(0.013)	(0.012)	(0.007)	(0.003)
European Socio-Economic Groups ("Less skilled employee" omitted)												
Managers	0.317***	0.204***	0.113***	0.073***	0.373***	0.149***	0.224***	0.063***	0.044	0.168***	–0.125***	0.072***
	(0.036)	(0.034)	(0.015)	(0.011)	(0.027)	(0.025)	(0.012)	(0.008)	(0.029)	(0.026)	(0.014)	(0.009)
Professionals	–0.052**	–0.19***	0.138***	–0.018***	0.101***	–0.133***	0.234***	–0.011**	–0.258***	–0.093***	–0.165***	–0.039***
	(0.022)	(0.02)	(0.013)	(0.006)	(0.017)	(0.015)	(0.01)	(0.004)	(0.020)	(0.016)	(0.013)	(0.005)
Technicians and associated professionals	–0.171***	–0.256***	0.085***	–0.047***	–0.182***	–0.316***	0.133***	–0.067***	–0.457***	–0.244***	–0.213***	–0.091***
	(0.015)	(0.013)	(0.011)	(0.005)	(0.015)	(0.013)	(0.010)	(0.003)	(0.015)	(0.011)	(0.012)	(0.003)

Table 4 (continued)

Clerks and skilled service employees	–0.225***	–0.191***	–0.033***	–0.055***	–0.288***	–0.283***	–0.005	–0.067***	–0.458***	–0.202***	–0.256***	–0.085***
	(0.014)	(0.011)	(0.012)	(0.003)	(0.013)	(0.01)	(0.011)	(0.003)	(0.015)	(0.009)	(0.013)	(0.002)
Industrial skilled employees	–0.235***	–0.195***	–0.04***	–0.052***	–.0228***	–0.186***	–0.042***	–0.055***	–0.487***	–0.190***	–0.297***	–0.086***
	(0.013)	(0.01)	(0.011)	(0.003)	(0.012)	(0.009)	(0.009)	(0.002)	(0.014)	(0.009)	(0.012)	(0.002)
Sectors (“Trade sector” omitted)												
Agriculture	–0.011	–0.059***	0.047**	–0.021***	0.332***	0.100***	0.232***	0.037***	–0.186***	–0.064***	–0.122***	–0.04***
	(0.022)	(0.016)	(0.019)	(0.005)	(0.028)	(0.021)	(0.02)	(0.005)	(0.025)	(0.016)	(0.022)	(0.004)
Industry	0.143***	0.067***	0.077***	0.021***	0.094***	0.034***	0.06***	0.013***	–0.033**	–0.034***	0.001	–0.014***
	(0.016)	(0.013)	(0.012)	(0.004)	(0.014)	(0.011)	(0.01)	(0.003)	(0.016)	(0.011)	(0.012)	(0.003)
Construction	0.084***	0.026	0.058***	0.01	0.155***	0.064***	0.091***	0.018***	–0.109***	–0.042**	–0.067***	–0.028***
	(0.021)	(0.017)	(0.016)	(0.007)	(0.018)	(0.015)	(0.013)	(0.004)	(0.021)	(0.017)	(0.015)	(0.005)
Low-skill service sector	0.174***	0.007	0.167***	0.011**	0.111***	–0.009	0.12***	0.009***	–0.054***	–0.051***	–0.003	–0.022***
	(0.016)	(0.013)	(0.013)	(0.004)	(0.015)	(0.011)	(0.011)	(0.003)	(0.018)	(0.012)	(0.014)	(0.004)
High-skill service sector	0.304***	0.185***	0.118***	.065***	0.19***	0.136***	0.054***	0.037***	0.163***	0.084***	0.079***	0.037***
	(0.021)	(0.018)	(0.013)	(0.007)	(0.018)	(0.015)	(0.011)	(0.005)	(0.02)	(0.016)	(0.014)	(0.005)
Public service	0.085***	–0.044***	0.129***	–0.011**	0.063***	0.011	0.051***	0.001	–0.219***	–0.192***	–0.027**	–0.064***
	(0.016)	(0.013)	(0.012)	(0.004)	(0.015)	(0.012)	(0.01)	(0.003)	(0.017)	(0.013)	(0.013)	(0.004)
Constant	1.624***	0.889***	0.735***	0.351***	1.268***	0.855***	0.413***	0.329***	1.692***	0.890***	0.802***	0.366***
	(0.024)	(0.018)	(0.019)	(0.007)	(0.023)	(0.016)	(0.018)	(0.004)	(0.031)	(0.018)	(0.027)	(0.005)
Observations	74,560	74,560	74,560	74,560	100,612	100,612	100,612	100,612	68,131	68,131	68,131	68,131
Avg. RIF	1.228	0. 683	0.545	0.288	1.351	0.775	0.575	0.315	1.144	0.571	0.573	0.260

Table 4 (continued)

Variables	Slovakia				Bulgaria				Romania			
	90–10	90–50	50–10	Gini	90–10	90–50	50–10	Gini	90–10	90–50	50–10	Gini
Female	–0.073***	–0.029***	–0.044***	–0.009***	–0.168***	–0.064***	–0.104***	–0.03***	–0.045***	0.044***	–0.089***	–0.001
	(0.008)	(0.007)	(0.006)	(0.002)	(0.012)	(0.011)	(0.006)	(0.004)	(0.012)	(0.011)	(0.008)	(0.003)
Married	0.030***	0.035***	–0.005	0.007***	0.023**	0.029***	–0.006	–0.004	0.006	–0.020*	0.026***	–0.002
	(0.008)	(0.007)	(0.006)	(0.002)	(0.012)	(0.011)	(0.007)	(0.004)	(0.012)	(0.012)	(0.009)	(0.003)
Education (“Lower secondary and below” omitted)												
Upper secondary education	–0.186***	–0.092***	–0.095***	–0.041***	–0.068***	–0.105***	0.037***	–0.030***	–0.038***	–0.079***	0.041***	–0.010***
	(0.023)	(0.011)	(0.021)	(0.006)	(0.014)	(0.012)	(0.011)	(0.005)	(0.014)	(0.012)	(0.014)	(0.003)
Tertiary education	0.031	0.005	0.026	0.004	0.199***	0.019	0.180***	0.030***	0.306***	0.015	0.291***	0.054***
	(0.026)	(0.015)	(0.022)	(0.007)	(0.022)	(0.020)	(0.014)	(0.008)	(0.026)	(0.024)	(0.019)	(0.005)
Health difficulty	0.066***	0.027***	0.039***	0.017***	–0.012	–0.020	0.008	–0.006	0.024	0.036**	–0.012	0.012**
	(0.010)	(0.007)	(0.007)	(0.002)	(0.021)	(0.019)	(0.013)	(0.007)	(0.017)	(0.016)	(0.013)	(0.005)
Experience	0.014***	0.007***	0.007***	0.003***	0.013***	0.005***	0.007***	0.004***	0.019***	0.007***	0.013***	0.004***
	(0.001)	(0.001)	(0.001)	(0.0001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.0001)
Experience^2	–0.029***	–0.014***	–0.014***	–0.007***	–0.025***	–0.012***	–0.013***	–0.007***	–0.038***	–0.016***	–0.022***	–0.007***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.004)	(0.003)	(0.002)	(0.001)	(0.004)	(0.004)	(0.003)	(0.001)
Permanent contract	–0.161***	–0.102***	–0.058***	–0.046***	–0.097***	–0.084***	–0.014	–0.036***	–0.066**	–0.063**	–0.003	–0.017**
	(0.013)	(0.008)	(0.010)	(0.004)	(0.019)	(0.017)	(0.013)	(0.008)	(0.032)	(0.029)	(0.023)	(0.007)
Supervisory	0.206***	0.161***	0.045***	0.045***	0.266***	0.169***	0.097***	0.063***	0.243***	0.119***	0.124***	0.060***
	(0.014)	(0.012)	(0.007)	(0.004)	(0.023)	(0.022)	(0.009)	(0.009)	(0.028)	(0.028)	(0.013)	(0.007)
European Socio–Economic Groups (“Less skilled employee” omitted)												
Managers	–0.024	0.048**	–0.072***	0.024***	0.341***	0.142***	0.199***	0.112***	0.266***	0.063	0.203***	0.062***
	(0.023)	(0.02)	(0.012)	(0.007)	(0.039)	(0.037)	(0.015)	(0.018)	(0.048)	(0.047)	(0.022)	(0.013)
Professionals	–0.283***	–0.152***	–0.130***	–0.064***	0.213***	0.057**	0.156***	0.056***	0.003	–0.164***	0.167***	–0.014**
	(0.015)	(0.012)	(0.010)	(0.004)	(0.025)	(0.023)	(0.013)	(0.009)	(0.027)	(0.026)	(0.017)	(0.006)
Technicians and associated professionals	–0.341***	–0.178***	–0.163***	–0.076***	0.079***	–0.024	0.103***	–0.006	–0.186***	–0.236***	0.050***	–0.048***
	(0.012)	(0.009)	(0.009)	(0.003)	(0.024)	(0.022)	(0.012)	(0.008)	(0.020)	(0.02)	(0.016)	(0.004)

Table 4 (continued)

Clerks and skilled service employees	–0.355***	–0.171***	–0.183***	–0.072***	–0.045***	–0.081***	0.036***	–0.020***	–0.108***	–0.077***	–0.031*	–0.026***
	(0.013)	(0.009)	(0.010)	(0.003)	(0.016)	(0.015)	(0.011)	(0.005)	(0.020)	(0.018)	(0.017)	(0.004)
Industrial skilled employees	–0.268***	–0.104***	–0.164***	–0.054***	–0.094***	–0.127***	0.033***	–0.032***	–0.133***	–0.097***	–0.037***	–0.021***
	(0.013)	(0.009)	(0.010)	(0.003)	(0.014)	(0.013)	(0.010)	(0.005)	(0.015)	(0.014)	(0.013)	(0.003)
Sectors ("Trade sector" omitted)												
Agriculture	–0.067***	–0.054***	–0.013	–0.009	–0.027	–0.028	0.001	–0.020***	0.090***	0.121***	–0.032	0.023***
	(0.025)	(0.017)	(0.021)	(0.011)	(0.026)	(0.023)	(0.019)	(0.008)	(0.032)	(0.028)	(0.025)	(0.006)
Industry	0.025*	–0.002	0.027***	0.002	0.104***	0.049***	0.055***	0.014**	0.027*	–0.019	0.046***	0.005
	(0.013)	(0.010)	(0.010)	(0.003)	(0.018)	(0.016)	(0.011)	(0.006)	(0.016)	(0.016)	(0.012)	(0.003)
Construction	–0.001	–0.029**	0.028**	–0.001	–0.090***	–0.094***	0.004	–0.003	0.040*	0.049**	–0.009	0.011**
	(0.018)	(0.015)	(0.014)	(0.004)	(0.022)	(0.021)	(0.015)	(0.010)	(0.021)	(0.020)	(0.016)	(0.006)
Low-skill service sector	0.04***	0.002	0.038***	0.008**	0.017	–0.021	0.038***	–0.003	0.008	0.011	–0.003	0.006
	(0.015)	(0.010)	(0.012)	(0.003)	(0.018)	(0.016)	(0.012)	(0.006)	(0.018)	(0.017)	(0.014)	(0.004)
High-skill service sector	0.195***	0.121***	0.074***	0.055***	0.240***	0.181***	0.059***	0.075***	0.162***	0.087***	0.075***	0.039***
	(0.017)	(0.014)	(0.011)	(0.005)	(0.026)	(0.024)	(0.013)	(0.011)	(0.025)	(0.024)	(0.015)	(0.006)
Public service	–0.027**	–0.048***	0.020**	–0.012***	–0.110***	–0.170***	0.06***	–0.059***	0.104***	0.084***	0.020	0.031***
	(0.013)	(0.010)	(0.010)	(0.003)	(0.020)	(0.019)	(0.012)	(0.007)	(0.020)	(0.019)	(0.014)	(0.004)
Constant	1.299***	0.650***	0.649***	0.295***	1.168***	0.868***	0.300***	0.328***	1.091***	0.843***	0.248***	0.262***
	(0.03)	(0.017)	(0.026)	(0.007)	(0.031)	(0.028)	(0.020)	(0.010)	(0.041)	(0.037)	(0.031)	(0.009)
Observations	58,663	58,663	58,663	58,663	52,702	52,702	52,702	52,702	50,283	50,283	50,283	50,283
Avg. RIF	0.959	0.475	.48403	0.218	1.226	0.729	0.498	0.313	1.260	0.7233	0.536	0.289

Source: Authors' calculation based on EU-SILC (Eurostat) data

Robust standard errors are in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

The effect of *permanent employment contract* declines monotonically as a function of percentiles in all selected countries, suggesting a more substantial impact on reducing inequality at lower quantiles. In particular, the slope of the permanent contract is steeper in the lower tail of the wage distribution in Hungary (Fig. 11 in the Appendix). The monotonic effect arises because it enhances both the magnitude and the dispersion of wages. Therefore, an increasing the proportion of individuals with permanent employment contracts leads to a decrease in all measures of wage inequality in the selected countries. This effect is particularly pronounced in Hungary, Czechia, and Slovakia (Table 4).

Supervisory responsibility and workers' health difficulties are the covariates that contribute to enhancing wage inequality in the selected countries Figure 11 in the Appendix presents that the impact of supervisory responsibility rises monotonically as a function of percentiles, meaning that increasing fraction of the workforce with supervisory responsibility has a greater impact on higher than lower quantiles in wage distribution. The slopes of supervisory responsibility for the selected nations are similar, showing that wage inequalities are consistent across countries. Therefore, a rise in the proportion of employees with supervisory responsibilities has a robust and statistically significant positive impact on all inequality measures across all countries. An increasing share of employees facing health difficulties tends to escalate wage inequality in Czechia, Slovakia, and Hungary. Health difficulties among workers substantially impact all wage gap measures in Czechia compared to other countries, especially at the lower end of the wage distribution. A one-percentage-point increase in the fraction of individuals with reduced activities due to health problems would result in a 24% expansion of the 50–10 log wage disparity in Czechia, three times higher than in Slovakia, the second most affected country. However, health difficulty is not statistically significant for all measures of inequality in Bulgaria and Poland, and for some measures in Romania (Table 4).

Educational attainment has an ambiguous effect on wage inequality in the selected countries The effect of *upper secondary education* declines across all percentiles in all selected countries except for Romania, while the impact of *tertiary education* rises with increasing percentiles in all selected countries except for Slovakia (Fig. 11 in the Appendix). As a result, a rise in the proportion of employees with upper secondary education has a statistically significant negative impact on all inequality measures across all countries (except Romania), with its effect particularly notable in Czechia, Slovakia, and Hungary. In contrast, an increase in the proportion of employees with tertiary education has a statistically significant positive impact on inequality measures in all countries except for Slovakia (Table 4). Nevertheless, the influence of tertiary education on wage distribution varies among countries. Increasing the fraction of employees with tertiary education has a larger impact on the higher end than the lower end of the wage distribution in Hungary and Poland. Meanwhile, it notably affects the lower tail of the wage distribution in Bulgaria and Romania (Table 4).

The coefficient on *experience* is positive, and the coefficient on *experience*^{2} is negative, implying an inverted U-shaped relationship between workers' experience and wage gaps. This suggests wage gaps widen in the years following the highest degree of education and then decrease (Table 4).

Marriage varies across the wage distribution and countries Figure 11 in the Appendix illustrates that marriage positively impacts wage levels in Poland, Romania, Hungary, and Czechia (above the 30th percentile), while it negatively impacts in Slovakia and Bulgaria. Additionally, the figure indicates non-monotonic effects across quantiles for Poland and Romania. Marriage increases wage inequality at the bottom of the distribution while decreasing inequality at the top in Poland and Romania. In Slovakia and Bulgaria, marriage exhibits contrasting behavior to that observed in Poland and Romania: it raises upper-tail wage inequality while having an insignificant impact on lower-tail wage inequality. In Czechia and Hungary (except for the 50–10 log wage gap), an increase in the proportion of married individuals leads to a rise in all wage inequality measures (Table 4).

5.2.2 European socio-economic groups (the combination of occupations and employment status)

As shown in Fig. 12 in the Appendix, a general pattern emerges in the selected countries as follows: there are increases in the returns to *managers* at the upper end of the wage distribution, and in the returns to *professionals* and *technicians* at the middle of the wage distribution. Conversely, there are reductions in the returns to *clerks, service*, and *industrial employees*. There are, nevertheless, slight discrepancies between countries.

In Hungary, Poland, Romania, and Bulgaria, the presence of managers raises wage levels consistently across quantiles in the wage distribution. However, the impact on wage inequality varies slightly due to differences in the slopes of the wage curves (Fig. 12 in the Appendix). Specifically, an increase in the share of managers has a more significant effect on the higher end than the lower end of the wage distribution in Hungary and Bulgaria, whereas it has a greater impact on the lower end than the higher end of the wage distribution in Poland and Romania. In contrast, in Czechia and Slovakia, managers exhibit slightly non-monotonic effects across the quantiles of the wage distribution. This implies that an increase in the share of managers decreases wage inequality at the lower end of the distribution but increases it at the higher end (Table 4).

Professionals and technicians have a non-monotonic impact across quantiles in the wage distributions in Hungary, Poland, and Romania (Fig. 12 in the Appendix). These two covariates exert the most significant impact in the middle of the wage distribution in these countries. This increases wage inequality at the lower tail of the distribution while contributing to an even greater decrease in inequality at the higher tail of the distribution (Table 4). On the other hand, the effects of these two occupations decline as percentiles in the wage distribution increase in Czechia and Slovakia, whereas in Bulgaria, they lead to a slight increase across quantiles (Fig. 12 in the Appedix). Therefore, an increase in the proportion of employees in these two occupations contributes to decreased wage inequality in Czechia and Slovakia, but it leads to an increase in inequality in Bulgaria (Table 4).

The effects of clerks, service, and industrial employees diminish monotonically across quantiles in all countries except for Bulgaria. This implies that the impacts of these two groups are more pronounced at lower quantiles than at higher quantiles in the wage distribution (Fig. 12 in the Appendix). Consequently, an increase in the proportion of employees with these two occupations leads to a decrease in wage inequality measures in these countries. However, their impacts on wage inequality exhibit slight variations due to differences in the slopes of the wage curves. Specifically, increasing the fraction of these two groups has a more substantial effect on the higher end than the lower end of the wage distribution in Hungary and Poland, whereas it has a greater impact on the lower end than the higher end of the wage distribution in Czechia and Slovakia. In Bulgaria, an increase in the share of two groups increases wage inequality at the lower end of the distribution but decreases it at the higher end (Table 4).

5.2.3 Sectors

As shown in Fig. 13 in the Appendix, the following general patterns are observed across the selected countries: there are rises in both the returns to the *high-skill service sector* at the upper end of the wage distribution and the returns to the *low-skill service sector* at the middle of the wage distribution. Compared to the reference category (the trade sector), returns to *agriculture*, *construction*, and *public service* are consistently lower across quantiles in some countries. The impact of these sectors exhibits a non-monotonic pattern across different quantiles. However, there are some discrepancies between countries.

The impact of the high-skill service sector increases monotonically as a function of percentiles in all countries, implying that the increasing fraction of employees in the high-skill sector has a more pronounced impact on higher quantiles of wage distribution than lower quantiles (Fig. 13 in the Appendix). As a result, a rise in the proportion of employees in the high-skill sector has a statistically significant positive impact on all measures of inequality across all countries (Table 4). Returns to the industrial sector increase throughout wage quantiles in Hungary, Poland, and Bulgaria but are non-monotonic across quantiles in Czechia, Slovakia, and Romania (Fig. 13 in the Appendix). As a result, an increase in the proportion of employees in the industrial sector contributes to an increase in wage inequality in Hungary, Poland, and Bulgaria but results in a decrease in the lower tail of the distribution and an increase in the upper tail of the distribution in Czechia, Slovakia, and Romania (Table 4).

The low-skill service sector has a non-monotonic impact across quantiles in the wage distributions in all countries except Czechia. Notably, it exerts its most substantial impact in the middle of the wage distribution in most countries, as illustrated in Fig. 13 in the Appendix. Consequently, increasing the fraction of employees in the low-skill service sector leads to a statistically significant increase in wage inequality at the lower tail of the distribution. However, this impact is not statistically significant at the higher tail of the distribution. In Czechia, increasing the number of employees in the low-skill service sector negatively affects wage inequality (Table 4).

The impacts of agriculture, construction, and public service on wage levels and wage inequality vary across countries. Figure 13 in Appendix illustrates the non-monotonic effects of these three sectors across different quantiles in Hungary, Slovakia, Romania, and Bulgaria. In contrast, in Poland, these sectors exert an increasing impact throughout wage quantiles, while in Czechia, their influence diminishes across quantiles. Specifically, augmenting the proportion of employees in these three sectors contributes to an increase in wage inequality at the lower end of the distribution while concurrently leading to a decrease in wage inequality at the higher end of the distribution in Hungary and Slovakia. Conversely, this pattern is reversed in Romania, where we found statistically significant increases in 90–50 log wage gaps. Examining global inequality metrics, such as the Gini index and the 90–10 log wage difference, finds that the agricultural sector has a negative impact on these measures in Hungary and Bulgaria but a positive impact in Slovakia and Romania. Furthermore, construction has a negative influence on these metrics in Slovakia and Bulgaria but a positive impact in Hungary and Romania. Except for Romania, three countries have a negative impact on public service. In Poland, the presence of these three sectors results in an increase in all measures of inequality. In contrast, in Czechia, their involvement leads to a decrease in all inequality measures (Table 4).

5.3 Decomposition analysis

The inequality decomposition analysis is conducted over two time periods, 2010 and 2019. Table 5 shows the decomposition results for the measures of wage inequality (the 90–10, 90–50, and 50–10 log wage gaps and the Gini index) for each country, applying the reweighting procedure. The specification errors shown in Table 5 are negligible and statistically insignificant across all models and countries, except for the 90–50 log wage gap difference in Poland and the 50–10 log wage gap difference in Hungary and Slovakia. This suggests that the RIF regressions yield highly accurate estimates of composition and wage structure effects. The reweighting error indicates a high–quality reweighting process, as it is minimal and not statistically different from zero across all models and countries.

The decomposition analysis conducted for the selected countries confirms the raw data's patterns in wage inequality evolution discussed in Section 5.1. The results support that inequality increased in Bulgaria and Hungary (except the 90–50 log wage gap) and decreased in Poland and Slovakia. In the cases of Czechia and Romania, changes in inequality measures are relatively minor, with some lacking statistical significance.

Countries where wage inequality declined between 2010 and 2019 Wage inequality measures reduced by 8 to 17 percent in Poland and 11 to 13 percent in Slovakia. The wage structure effect dominates the explanations for reducing wage inequality in these countries. Thus, rather than changes in covariates, the generally observed pattern of decreasing wage inequality resulted from bigger changes in returns to covariates. This result is consistent with the findings of Magda et al. (2021), who found that wage structure effects led to wage inequality decreases in the CEE countries. Furthermore, wage structure impacts are greatest at the bottom of the wage distribution and diminish as one moves up the wage distribution. There is a trend in these countries toward a more homogeneous level of the covariates' rewards across the wage distribution.

In Poland, several key factors play a pivotal role in the reduction of wage structural effects, notably, the women's effect (90–10, 90–50, and Gini), returns to education (90–10, 50–10, and Gini), and returns to the permanent employment contract (90–10 and 90–50). Among these, the most significant contributor to the reductions observed in wage inequality measures (90–10, 50–10, and Gini) is the decline in returns to education. Regarding compositional effects, they are significant across all inequality measures except for the 50–10 log wage gap. Despite being of a lesser magnitude, other forces may act in the opposite direction, increasing wage disparities. Primary drivers behind these movements include workers' educational and socioeconomic (ESeG) advancements, accumulated experience gains, and progress at the sectoral level. Furthermore, no evidence supports the skill-biased technology hypothesis (Acemoglu 2002) in Poland. This inconsistency arises from the fact that while workers' educational upgrading happens in the compositional change, there are diminishing returns to education in the structure change.

In Slovakia, fewer statistically significant factors explain the reduction of wage structural effects on the wage distribution. The estimated constants (unknown factors) are the primary explanation for the structure effect in the change in the 90–10 and 90–50 log wage gaps, whereas the women's effect contributes to the structural change in the 50–10 log wage gap. The compositional effects are statistically significant for the 90–50 log wage gap and the Gini index, and they align in the same direction as structural effects, contributing to the reduction of wage inequality. The compositional changes are explained by the shifts in the percentage of workers with permanent employment contracts, those with supervisory

Table 5 Detailed decomposition of wage inequality change with reweighing

	Hungary (2010–2019)				Poland (2010–2019)				Czechia (2010–2019)			
Inequality measures	90–10	90–50	50–10	Gini	90–10	90–50	50–10	Gini	90–10	90–50	50–10	Gini
Total difference	0.210***	–0.122***	0.332***	0.016*	–0.165***	–0.061***	–0.104***	–0.033***	0.033*	–0.006	0.039***	–0.001
	(0.058)	(0.028)	(0.052)	(0.010)	(0.020)	(0.018)	(0.013)	(0.005)	(0.019)	(0.015)	(0.014)	(0.004)
Composition effect	–0.093***	–0.044***	–0.049*	–0.018***	0.021***	0.024***	–0.003	0.003***	0.016**	0.021***	–0.005	0.004***
	(0.027)	(0.011)	(0.025)	(0.004)	(0.007)	(0.006)	(0.004)	(0.001)	(0.008)	(0.006)	(0.005)	(0.001)
Wage structure	0.304***	–0.078**	0.382***	0.034***	–0.185***	–0.085***	–0.101***	–0.036***	0.016	–0.027*	0.044***	–0.004
	(0.050)	(0.031)	(0.040)	(0.011)	(0.020)	(0.018)	(0.013)	(0.005)	(0.020)	(0.015)	(0.015)	(0.004)
Composition Effects												
Female	0.003*	0.001	0.002*	0.0004*	–0.004***	–0.001***	–0.002***	–0.001***	–0.004***	–0.002***	–0.001	–0.001***
	(0.002)	(0.001)	(0.001)	(0.0003)	(0.001)	(0.0005)	(0.0004)	(0.0001)	(0.001)	(0.001)	(0.001)	(0.0002)
Married	–0.017***	–0.008***	–0.010*	–0.003***	–0.001	–0.0004	–0.001*	–0.0001	–0.003	–0.002	–0.001	–0.0001
	(0.006)	(0.003)	(0.005)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.0002)	(0.002)	(0.001)	(0.001)	(0.0004)
Education	0.011	0.006	0.005	0.004*	0.014***	0.005	0.010***	0.003***	0.021***	0.018***	0.004*	0.004***
	(0.008)	(0.004)	(0.007)	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.001)
Health difficulty	–0.003	–0.001	–0.002	–0.001	–0.0001	–0.0001	–0.00002	–0.00001	0.005***	0.002***	0.004***	0.001***
	(0.002)	(0.001)	(0.001)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.00007)	(0.001)	(0.001)	(0.001)	(0.0002)
Experience	–0.024***	–0.006*	–0.018**	–0.002*	0.006***	0.003	0.004***	0.002***	0.003***	0.002**	0.001	0.001***
	(0.008)	(0.003)	(0.007)	(0.001)	(0.002)	(0.002)	(0.001)	(0.0005)	(0.0010	(0.001)	(0.001)	(0.0002)
ESeG	–0.009	–0.006	–0.003	–0.003	0.005*	–0.005**	0.010***	–0.0003	0.003	0.006	–0.003	0.001
	(0.015)	(0.006)	(0.014)	(0.002)	(0.002)	(0.002)	(0.002)	(0.0006)	(0.005)	(0.004)	(0.003)	(0.001)
Permanent contract	–0.093****	–0.017***	–0.076***	–0.013***	–0.008***	–0.004***	–0.004***	–0.002***	–0.008***	–0.002**	–0.006***	–0.002***
	(0.012)	(0.003)	(0.011)	(0.002)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.002)	(0.001)	(0.001)	(0.0003)
Supervisory	–0.015***	–0.007***	–0.008*	–0.001	0.0001	0.0001	0.0001	0.00004	–0.002**	–0.002**	0.0002	–0.001***
	(0.005)	(0.003)	(0.004)	(0.001)	(0.0003)	(0.0001)	(0.0002)	(0.00006)	(0.001)	(0.001)	(0.001)	(0.0002)
Sector	0.003	0.003	0.001	0.001	0.004***	0.004***	–0.001	0.001***	–0.007***	–0.003*	–0.004**	–0.001***
	(0.005)	(0.002)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.002)	(0.002)	(0.002)	(0.0004)

Table 5 (continued)

Specification error	0.050	–0.009	0.059**	–0.0003	0.004	0.023***	–0.019	0.0005	0.007	0.006	0.002	0.001
	(0.030)	(0.006)	(0.030)	(0.002)	(0.005)	(0.005)	(0.003)	(0.0005)	(0.005)	(0.005)	(0.004)	(0.0004)
Wage Structure Effects												
Female	–0.023	0.031	–0.054	–0.007	–0.082***	–0.062***	–0.020	–0.018***	–0.027	–0.033**	0.006	–0.004
	(0.053)	(0.032)	(0.044)	(0.011)	(0.022)	(0.020)	(0.014)	(0.006)	(0.020)	(0.015)	(0.015)	(0.004)
Married	0.107*	0.063*	0.044	0.022*	0.126***	0.101***	0.025	0.027***	–0.008	0.013	–0.021	–0.009*
	(0.058)	(0.036)	(0.047)	(0.013)	(0.034)	(0.031)	(0.022)	(0.009)	(0.025)	(0.020)	(0.019)	(0.005)
Education	–0.135	0.058	–0.193	0.020	–0.248***	–0.072	–0.175***	–0.034**	0.040	0.043	–0.003	0.014
	(0.146)	(0.071)	(0.127)	(0.029)	(0.075)	(0.056)	(0.064)	(0.015)	(0.100)	(0.038)	(0.096)	(0.014)
Health difficulty	0.019	0.005	0.014	0.008	–0.007	–0.007	–0.001	–0.002	0.019***	0.003	0.017***	0.001
	(0.019)	(0.010)	(0.018)	(0.007)	(0.006)	(0.006)	(0.004)	(0.002)	(0.005)	(0.003)	(0.005)	(0.001)
Experience	–0.306*	–0.159	–0.146	–0.052*	–0.093	–0.086	–0.006	–0.018	0.070	0.019	0.051	0.034**
	(0.175)	(0.100)	(0.151)	(0.031)	(0.063)	(0.057)	(0.038)	(0.016)	(0.071)	(0.056)	(0.053)	(0.015)
ESeG	0.092	0.099*	–0.007	0.018	0.002	–0.022	0.024	0.007	–0.114**	–0.028	–0.086**	–0.013*
	(0.098)	(0.056)	(0.085)	(0.018)	(0.039)	(0.032)	(0.031)	(0.009)	(0.046)	(0.026)	(0.041)	(0.008)
Permanent contract	–0.728***	–0.223***	–0.505***	–0.169***	–0.065*	–0.009	–0.056**	–0.011	–0.119*	–0.003	–0.116**	–0.012
	(0.144)	(0.073)	(0.123)	(0.043)	(0.035)	(0.029)	(0.025)	(0.008)	(0.067)	(0.039)	(0.057)	(0.012)
Supervisory	0.024	0.007	0.018	–0.007*	0.016	0.008	0.009	0.004	–0.041***	–0.022**	–0.019***	–0.007**
	(0.026)	(0.016)	(0.021)	(0.004)	(0.013)	(0.012)	(0.006)	(0.003)	(0.011)	(0.010)	(0.007)	(0.003)
Sector	–0.186	–0.013	–0.173	–0.021	0.098*	0.073*	0.026	0.023*	0.147**	0.055	0.092*	0.024**
	(0.141)	(0.080)	(0.123)	(0.023)	(0.051)	(0.044)	(0.037)	(0.012)	(0.060)	(0.040)	(0.048)	(0.012)
Constant	1.439***	0.055	1.384***	0.224***	0.070	–0.005	0.075	–0.014	0.045	–0.077	0.122	–0.034
	(0.319)	(0.157)	(0.274)	(0.053)	(0.110)	(0.089)	(0.086)	(0.025)	(0.150)	(0.078)	(0.136)	(0.025)
Reweighting error	–0.001	–0.001	0.0002	–0.001	–0.003	–0.002	–0.002	–0.001	0.006	0.004	0.001	0.001
	(0.015)	(0.007)	(0.010)	(0.003)	(0.005)	(0.003)	(0.003)	0.001	(0.006)	(0.004)	(0.003)	(0.001)

Table 5 (continued)

	Slovakia (2010–2019)				Bulgaria (2010–2019)				Romania (2010–2019)			
Inequality measures	90–10	90–50	50–10	Gini	90–10	90–50	50–10	Gini	90–10	90–50	50–10	Gini
Total difference	–0.114***	–0.060***	–0.054***	–0.032***	0.296***	0.180***	0.117***	0.075***	0.002	–0.018	0.020	–0.040***
	(0.020)	(0.016)	(0.014)	(0.005)	(0.032)	(0.029)	(0.016)	(0.009)	(0.024)	(0.023)	(0.014)	(0.006)
Composition effect	–0.009	–0.016**	0.007	–0.003*	–0.017	–0.013	–0.004	–0.003	–0.004	–0.006	0.003	0.001
	(0.008)	(0.007)	(0.005)	(0.002)	(0.011)	(0.011)	(0.006)	(0.003)	(0.008)	(0.007)	(0.005)	(0.001)
Wage structure	–0.105***	–0.044**	–0.061***	–0.029***	0.314***	0.192***	0.121***	0.079***	0.006	–0.012	0.017	–0.041***
	(0.022)	(0.018)	(0.015)	(0.005)	(0.034)	(0.031)	(0.017)	(0.009)	(0.026)	(0.024)	(0.015)	(0.006)
Composition Effects												
Female	0.0001	–0.0001	0.0002	0.00004	–0.003**	–0.001	–0.002**	0.0003	–0.001*	–0.0001	–0.001**	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.001)	(0.001)	(0.001)	(0.0002)	(0.001)	(0.001)	(0.0001)	(0.0001)
Married	–0.004**	–0.004**	0.00001	–0.0002	–0.005	–0.005	–0.0002	0.001	0.001	0.001	–0.0003	0.0002
	(0.002)	(0.001)	(0.001)	(0.0006)	(0.005)	(0.005)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.0003)
Education	0.002**	0.001**	0.001**	0.001*	0.007***	0.002	0.005***	0.001	0.008***	0.001	0.007***	0.0004
	(0.001)	(0.0004)	(0.001)	(0.0003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.0023)	(0.002)	(0.001)
Health difficulty	–0.0001	–0.0002	0.0001	–0.0003	–0.001*	–0.0004	–0.001*	–0.0001	–0.0002	0.0003	–0.0005*	0.0001
	(0.001)	(0.001)	(0.001)	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.00005)	(0.0003)	(0.0003)	(0.0003)	(0.0001)
Experience	–0.0001	0.0005	–0.001	0.0003	–0.007*	–0.005	–0.002	–0.0009	–0.002	–0.0023	0.0001	–0.0001
	(0.002)	(0.002)	(0.002)	(0.0005)	(0.004)	(0.003)	(0.002)	(0.0007)	(0.003)	(0.003)	(0.002)	(0.0007)
ESeG	0.006	0.002	0.004	0.001	–0.012**	–0.008*	–0.004	–0.002	–0.002	–0.003	0.001	–0.0001
	(0.005)	(0.004)	(0.003)	(0.001)	(0.005)	(0.005)	(0.003)	(0.001)	(0.005)	(0.005)	(0.003)	(0.001)
Permanent contract	–0.004***	–0.001**	–0.003***	–0.001***	–0.005**	–0.004**	–0.001	–0.004***	0.001	–0.0001	0.001	0.0001
	(0.001)	(0.001)	(0.001)	(0.0004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)
Supervisory	–0.011***	–0.009***	–0.002**	–0.002***	–0.003**	–0.003**	–0.0003	0.0002	–0.002	–0.001	–0.0007	–0.0002
	(0.002)	(0.002)	(0.001)	(0.0004)	(0.002)	(0.002)	(0.0003)	(0.0002)	(0.001)	(0.001)	(0.0005)	(0.0001)
Sector	–0.002	–0.0001	–0.002	–0.001	0.007	0.007	0.001	0.0002	–0.004	–0.002	–0.003	0.0006
	(0.003)	(0.002)	(0.002)	(0.0008)	(0.005)	(0.004)	(0.002)	(0.0013)	(0.003)	(0.003)	(0.002)	(0.0006)

Table 5 (continued)

Specification error	0.004	–0.005	0.009***	0.001	0.004	0.004	0.0003	0.001	–0.001	–0.0002	–0.0006	0.0004
	(0.005)	(0.005)	(0.003)	(0.0004)	(0.005)	(0.005)	(0.004)	(0.001)	(0.005)	(0.004)	(0.004)	(0.001)
Wage Structure Effects												
Female	0.017	0.047**	–0.030*	0.0002	–0.089***	–0.056*	–0.033**	–0.012	0.004	0.005	–0.001	–0.005
	(0.024)	(0.019)	(0.016)	(0.006)	(0.033)	(0.031)	(0.016)	(0.009)	(0.023)	(0.022)	(0.013)	(0.005)
Married	0.044	0.030	0.013	0.002	0.038	0.058	–0.020	0.001	–0.053	–0.038	–0.015	–0.011
	(0.032)	(0.026)	(0.022)	(0.009)	(0.046)	(0.044)	(0.024)	(0.014)	(0.042)	(0.040)	(0.024)	(0.009)
Education	–0.058	–0.015	–0.043	–0.061	0.105	–0.058	0.163***	0.014	0.011	–0.123**	0.134**	–0.011
	(0.134)	(0.075)	(0.113)	(0.065)	(0.078)	(0.066)	(0.057)	(0.028)	(0.069)	(0.058)	(0.060)	(0.014)
Health difficulty	–0.012	–0.005	–0.008	–0.002	–0.013***	–0.006	–0.007**	–0.002**	0.003	0.003	0.001	0.001
	(0.012)	(0.009)	(0.008)	(0.003)	(0.005)	(0.005)	(0.003)	(0.001)	(0.007)	(0.006)	(0.004)	90.002)
Experience	0.047	0.054	–0.007	0.007	0.080	–0.007	0.087	–0.004	–0.132	–0.052	–0.081	–0.021
	(0.072)	(0.057)	(0.050)	(0.018)	(0.114)	(0.111)	(0.064)	(0.032)	(0.107)	(0.103)	(0.056)	(0.026)
ESeG	0.089*	0.011	0.078**	0.027**	0.094*	0.058	0.035	0.022	–0.009	0.032	–0.041	0.022**
	(0.048)	(0.031)	(0.038)	(0.012)	(0.054)	(0.051)	(0.033)	(0.014)	(0.054)	(0.050)	(0.036)	(0.010)
Permanent contract	–0.010	0.015	–0.025	–0.012	–0.056	–0.082	0.026	0.016	–0.347***	–0.278**	–0.069	–0.024
	(0.075)	(0.048)	(0.059)	(0.024)	(0.100)	(0.093)	(0.062)	(0.027)	(0.125)	(0.124)	(0.092)	(0.027)
Supervisory	0.023*	0.025**	–0.002	0.002	0.021	0.027	–0.006	0.0002	0.001	0.003	–0.002	–0.003
	(0.013)	(0.011)	(0.005)	(0.003)	(0.018)	(0.018)	(0.006)	(0.005)	(0.011)	(0.011)	(0.004)	(0.003)
Sector	0.028	0.046	–0.018	–0.006	–0.052	–0.059	0.007	–0.011	0.084	0.037	0.047	0.011
	(0.066)	(0.049)	(0.046)	(0.012)	(0.080)	(0.076)	(0.045)	(0.018)	(0.052)	(0.051)	(0.035)	(0.012)
Constant	–0.274***	–0.253**	–0.021	0.013	0.185*	0.315*	0.130*	0.053	0.444***	0.401**	0.043	–0.0001
	(0.110)	(0.113)	(0.145)	(0.074)	(0.108)	(0.163)	(0.071)	(0.045)	(0.173)	(0.166)	(0.123)	(0.041)
Reweighting error	0.001	0.001	0.001	0.001	0.002	0.003	0.001	0.001	0.00005	–0.001	0.001	–0.0001
	(0.006)	(0.004)	(0.002)	(0.001)	(0.013)	(0.010)	(0.006)	(0.002)	(0.008)	(0.005)	(0.005)	(0.001)

Source: Authors' calculation based on EU-SILC (Eurostat) data

Robust standard errors are in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

responsibilities, and married individuals. Additionally, significant educational upgrading among workers is observed in the composition effects across all inequality measures. This situation of workers' educational upgrade, coupled with no significant differences in the returns to education in the wage structure effect, aligns with the skill–biased technological change hypothesis.

Countries where wage inequality increased between 2010 and 2019 In Bulgaria, wage inequality measures experienced an increase ranging from 24 to 27 percent. Hungary's situation stands out from that of other countries. The 90–10 and 50–10 log wage disparities, along with the Gini index, expanded significantly, particularly at the lower end of the wage distribution (by 62%), while the 90–50 wage disparity diminished.

In Bulgaria, the wage structure effect emerges as the primary driver behind increased inequality across all measures, with its most pronounced impact observed at the top of the wage distribution. The changes in returns to socioeconomic groups and returns to education are more homogenous and significant explanations for the wage structural changes in the 90–10 and 50–10 log wage gaps, respectively. Change in estimated constants (unknown factor) contributes to a more significant portion of the wage inequality change in the 90–10, 90–50, and 50–10 log wage gaps. While composition effects are not statistically significant for all inequality measures in Bulgaria, there is some influence from compositional changes on workers' educational levels, exerting upward pressure on wage inequality, particularly in the 90–10 and 50–10 measures. Moreover, there is no evidence of declining returns to education in structure effects (as they are not significant). Consequently, it can be inferred that Bulgaria aligns with the skill-biased technology hypothesis.

In Hungary, the wage structure effect dominates in explaining increasing and reducing wage inequality. The increased wage inequality observed in the 90–10 and 50–10 log wage gaps and the Gini index is primarily attributed to increases in the rewards for worker characteristics (a positive wage structure effect). Conversely, the reduction in wage inequality in the 90–50 log wage gap is mainly associated with decreases in the rewards for worker characteristics (a negative wage structure effect). The changes in estimated constants thoroughly explain the increases of structural effect in the 90–10 and 50–10 wage gaps and the Gini index. This suggests that unknown factors contribute to the rising wage inequality in Hungary. While the composition effects are statistically significant for the increases in wage inequality (90–10, 50–10, and Gini), they operate in the opposite direction of the wage structure, contributing to the narrowing of the wage gap. These effects are primarily explained by alterations in the percentage of married individuals, workers with permanent employment contracts, workers with supervisory duties, and worker's experience.

Concerning the reduction in the upper tail of the wage distribution in Hungary, the change in returns to permanent employment contracts primarily accounts for the structural change in the 90–50 log wage gap. Meanwhile, the changes in the percentage of workers with permanent contracts, married individuals, workers with supervisory duties, and worker's experience are the key factors explaining the compositional change in the 90–50 log wage gap. There is no indication of skill-biased technological change in Hungary. This result is also consistent with the findings of Pereira & Galego (2019), who faced no evidence of a skill-biased technological change hypothesis in the movement of wage disparity in Hungary.

Countries where wage inequality changed relatively minor between 2010 and 2019 In Czechia and Romania, inequality measures have undergone relatively slight changes, some of which are not statistically significant. Changes in the 90–10 and 50–10 log wage gaps in Czechia between 2010 and 2019 are statistically significant, increasing by 3 percent and 8 percent, respectively. The rise in the 90–10 log wage gap is primarily attributed to an increase in employment composition (positive compositional effect), while the increase in the lower end of wage distribution (50–10) is associated with the rise in the rewards for worker characteristics (positive wage structure effect). The increase in the composition effect is explained by shifts in the percentage of workers with health difficulties and upgrades in workers' education and experience. In contrast, the sectorial wage premium and the returns to health difficulties explain the increase in the wage structural effect. However, for all inequality measures in Czechia, there is evidence of skill-biased technological change, as the average level of education among workers increased (composition effect), and there is no indication of falling returns to education, as the wage structure effect is not significant.

The findings for Romania reveal a statistically significant decrease in the Gini index, indicating a 14 percent reduction from 2010 to 2019. This decline is attributed to the impact of the wage structure effect. Notably, changes in wage inequality across the distribution (90–10, 90–50, and 50–10) during this period, and the associated composition and structure effects, are not statistically significant. However, an influence stems from shifts in the composition of workers' educational levels, contributing to upward pressure on the 90–10 and 50–10 log wage gaps. This pattern aligns with the skill-biased technological change hypothesis, as it corresponds to significant upgrading in workers' education levels, coupled with no significant decrease in the returns to education in the structure effects.

The role of the minimum wage Overall, the findings reveal that movements in wage disparities in Hungary, Slovakia, Bulgaria, and Romania can be attributed to unidentified factors represented by estimated constants. Furthermore, the micro determinants analyzed do not adequately account for the notable changes in wage structure effects observed in Slovakia and Bulgaria. These findings lead us to assume that a change in the real value of minimum wage could affect variations in inequality and consequently influence the decomposition. Between 2010 and 2019, the real minimum wage in these countries increased dramatically (Fig. 2). Raising the minimum wage is typically supposed to increase incomes for many low-paid workers, reducing wage inequality. Studies indicate that alterations in the minimum wage influence wage inequality at the bottom of the wage distribution (Autor et al. 2016). Therefore, we anticipate that changes in the minimum wage will specifically affect the 50–10 and 90–10 log wage gaps. Given that the Gini index encompasses inequality throughout the entire wage distribution, changes in the minimum wage are also more likely to be discerned through the Gini index.

When assessing the impact of the minimum wage on changes in inequality, we distinguish between contributions resulting from market forces (compositional and/or structural effects) and those specifically driven by the minimum wage. To further elaborate, we conducted a decomposition of wage inequality changes, considering the real value of the minimum wage at its initial-year value (see Eq. 17). This decomposition reveals the contribution of factors other than minimum wages to the changes in inequality. Subsequently, the contribution of the minimum wage to changes in wage inequality is defined as the difference between the results obtained from the previous decomposition (Table 5), which does not control for changes in the minimum wage, and the results from this decomposition (Table 7) that control for changes in the minimum wage.

In terms of methodology, examining the influence of changing the value of the minimum wage on the variations in inequality is similar to the RIF decomposition technique described in Section 3. One distinction is that the counterfactual wage distribution is generated assuming that the real minimum wage at time $t = 1$ is the same as its level (r_0) at time $t = 0$. In deriving this distribution, the part of the wage distribution of $t = 0$ for wages at or below r_0 is combined with the part of wage distribution of $t = 1$ for wages above r_0. Following (10), the decomposition of the change in the distributional statistic while holding the real minimum wage constant is as follows:

$$\Delta v^{r_0} = \underbrace{\left(v_1^{r_0} - v_r\right)}_{\substack{wage\ structure \\ effect}} + \underbrace{\left(v_r - v_0^{r_0}\right)}_{\substack{composition \\ effect}} \tag{17}$$

where, v_r is the counterfactual statistic on the reweighted sample with constant minimum wage. Nevertheless, the reweighing approach utilized in the RIF decomposition by (DiNardo et al. 1996) entails robust assumptions regarding the minimum wage. These assumptions include the non-existence of spillover effects on the wage distribution to the right of the minimum wage, the conditional density's reliance on the real value of the minimum wage for shaping real wages at or below the minimum wage, and the lack of employment effects resulting from alterations in minimum wages.

Concerning the minimum wage's employment implications, Neumark & Wascher's (2007) extensive investigation revealed that minimum wage policies adversely affected employment, particularly leading to a decrease in job opportunities for low-skilled workers. Furthermore, the evidence for spillovers, particularly at the lower end of the distribution, is inconclusive, as some studies (e.g., Autor et al. 2016) find supportive results while others (e.g., Stewart 2012) do not. There are also other findings about spillovers, such as the potential that estimated spillovers are caused by measurement errors rather than actual effects (Autor et al. 2016) and the influence of altering minimum wages on relative wages is concentrated slightly above the minimum wage binding point (Teulings 2003). Based on these findings, our estimations of the impact of changes in the minimum wage on changes in inequality may be susceptible to bias.

Table 6 presents the contribution of minimum wage changes to inequality shifts. The results indicate that minimum wage changes have played a role in inequality changes in Hungary (90–10, 50–10, and Gini), Slovakia (90–10 and Gini), and Bulgaria (90–10 and 50–10). However, no statistically significant contribution has been identified for Poland, Czechia, and Romania. The alterations in the minimum wage account for around 54% and 33% of the shifts in the 90–10 and 50–10 log wage gaps in Hungary, 53% and 62% of the change in the 90–10 log wage gap, as well as the Gini index in Slovakia, and 9% and 15% of the changes in the 90–10 and 50–10 log wage gaps in Bulgaria.

Table 7 displays the decomposition of wage inequality change, incorporating the initial-year real value of the minimum wage for estimations in the three countries where the contribution of the minimum wage is identified. When comparing these results with the previous decomposition outcomes presented in Table 5, it becomes apparent that, accounting for changes in the minimum wage substantially diminishes the estimated constants in Hungary. Specifically, there is a noteworthy reduction from 1.44 to 0.59 for the alteration in the 90–10 log wage gap and from 1.38 to 0.52 for the change in the 50–10 log wage gap. Still, it preserves its importance (highly significant) for two measures.[5] Even after allowing for the effect of changes in the minimum wage, the estimated constant remains the

[5] Upon controlling for the variation in the minimum wage, the change in the Gini index does not demonstrate statistical significance (Table 7).

Table 6 Minimum wage's contribution to wage inequality change

		Hungary	Poland	Czechia	Slovakia	Bulgaria	Romania
90–10	Total	0.114*** (**54%**)	-0.029	-0.024	-0.061*** (**53%**)	0.027*** (**9%**)	-0.015
		(0.050)	(0.025)	(0.032)	(0.020)	(0.002)	(0.013)
	Composition	-0.022	0.029	-0.004	0.030***	-0.003	-0.052
		(0.023)	(0.023)	(0.030)	(0.015)	(0.003)	(0.030)
	Structure	0.135***	-0.074	-0.020	-0.075***	0.030***	0.037
		(0.038)	(0.048)	(0.015)	(0.022)	(0.003)	(0.026)
90–50	Total	0.004	-0.038	-0.002	-0.009	0.009	0.0003
		(0.007)	(0.022)	(0.001)	(0.005)	(0.006)	(0.004)
	Composition	0.006	0.027***	-0.001	-0.001	0.0003	0.006
		(0.005)	(0.005)	(0.001)	(0.002)	(0.003)	(0.004)
	Structure	-0.001	-0.064	-0.001	-0.007	0.010***	-0.006
		(0.007)	(0.040)	(0.002)	(0.005)	(0.002)	(0.006)
50–10	Total	0.109*** (**33%**)	-0.055	-0.022	-0.052	0.017*** (**15%**)	-0.015
		(0.048)	(0.036)	(0.013)	(0.030)	(0.001)	(0.020)
	Composition	-0.028	0.002	-0.003	0.016	-0.003***	-0.058
		(0.023)	(0.002)	(0.038)	(0.009)	(0.001)	(0.031)
	Structure	0.137***	-0.057	-0.019	-0.068	0.020***	0.043
		(0.036)	(0.035)	(0.021)	(0.050)	(0.001)	(0.040)
Gini	Total	0.029***	-0.036	-0.005	-0.020*** (**62%**)	-0.002	-0.032
		(0.003)	(0.021)	(0.004)	(0.001)	(0.001)	(0.025)
	Composition	0.005***	0.005***	0.002	0.001***	0.002	0.006
		(0.002)	(0.001)	(0.018)	(0.0001)	(0.001)	(0.004)
	Structure	0.024***	-0.040	-0.007	-0.021***	-0.002	-0.038
		(0.003)	(0.036)	(0.050)	0.001	(0.002)	(0.030)

Standard errors are in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.1

Notes: A generalized Hausman specification test is employed to compare the coefficients between models. The percentage contribution of the minimum wage change to the change in inequality is highlighted in bold within parentheses

Source: Authors' calculation based on EU-SILC (Eurostat) data

significant determinant in explaining the change in the 90–10 and 50–10 log wage gaps, as well as the Gini index. This is an undetermined wage increase, regardless of the worker's characteristics.

The adjustment of wages in Hungary might be impacted by spillover effects resulting from an increased minimum wage. When examining the increase in wages situated just above the minimum wage in the distribution from 2010 to 2019, it becomes evident that the minimum wage has experienced more growth than wages within that range. To illustrate, the equivalent hourly minimum wage has risen by approximately 76% from 2010 to 2019, surpassing the growth rate of the median hourly wage, which has increased by about 41% (Table 2). This observation suggests the potential existence of positive spillovers, as the pressure to restore wage differentials may rise with the proportion of workers

Table 7 Detailed decomposition of wage inequality changes with constant minimum wage

Variables	Hungary (2010–2019)			Slovakia (2010–2019)		Bulgaria (2010–2019)	
	90–10	50–10	Gini	90–10	Gini	90–10	50–10
Total difference	0.097***	0.223***	-0.013	-0.053***	-0.012**	0.270***	0.099***
	(0.031)	(0.018)	(0.009)	(0.020)	(0.005)	(0.031)	(0.016)
Composition effect	-0.071***	-0.022**	-0.023***	-0.024***	-0.004***	-0.014	-0.002
	(0.013)	(0.009)	(0.003)	(0.008)	(0.002)	(0.011)	(0.007)
Wage structure	0.168***	0.245***	0.010	-0.029	-0.008	0.284***	0.101***
	(0.033)	(0.018)	(0.010)	(0.023)	(0.005)	0.034)	(0.017)
Composition Effects							
Female	0.001*	0.001*	0.0003	-0.0001	-0.00001	-0.002	-0.001
	(0.001)	(0.0005)	(0.0002)	(0.0001)	(0.00003)	(0.001)	(0.001)
Married	-0.019***	-0.011***	-0.003***	-0.005**	-0.0002	-0.004	0.001
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.005)	(0.002)
Education	0.005*	0.002	0.002	0.001*	0.0004	0.007***	0.005***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.002)	(0.001)
Health difficulty	-0.001	0.0002	-0.001*	-0.002	-0.001**	-0.001*	0.0005*
	(0.001)	(0.0004)	(0.0003)	(0.001)	(0.0003)	(0.0004)	(0.0003)
Experience	-0.027***	-0.021***	-0.004***	-0.002	-0.001	-0.006	-0.001
	(0.003)	(0.003)	(0.001)	(0.002)	(0.0005)	(0.004)	(0.002)
ESeG	-0.022***	-0.014***	-0.005**	0.008*	0.002	-0.010**	-0.003
	(0.007)	(0.004)	(0.002)	(0.005)	(0.001)	(0.005)	(0.003)
Permanent contract	-0.040***	-0.023***	-0.012***	-0.003***	-0.001***	-0.005**	-0.001
	(0.005)	(0.003)	(0.002)	(0.001)	(0.0003)	(0.002)	(0.001)
Supervisory	-0.011***	-0.002	-0.002	-0.012***	-0.002***	-0.002	-0.0002
	(0.004)	(0.001)	(0.001)	(0.002)	(0.0005)	(0.002)	(0.0002)
Sector	0.007***	0.003**	0.001*	-0.007**	-0.002**	0.007	0.001
	(0.003)	(0.002)	(0.001)	(0.003)	(0.001)	(0.004)	(0.002)
Specification error	0.014	0.012	-0.0002	-0.002	0.0004	0.002	-0.002
	(0.012)	(0.011)	(0.002)	(0.005)	(0.0005)	(0.004)	(0.004)
Wage Structure Effects							
Female	0.008	-0.019	-0.001	0.023	0.003	-0.093***	-0.031*
	(0.034)	(0.018)	(0.011)	(0.024)	(0.006)	(0.033)	(0.016)
Married	0.103***	0.024	0.021*	0.057*	0.003	0.043	-0.020
	(0.037)	(0.021)	(0.012)	(0.032)	(0.008)	(0.046)	(0.024)
Education	0.018	-0.034	0.020	0.034	-0.051	0.130*	0.177**
	(0.076)	(0.055)	(0.026)	(0.134)	(0.057)	(0.078)	(0.057)
Health status	0.007	0.001	0.009	0.008	0.001	-0.014***	-0.008**
	(0.010)	(0.007)	(0.007)	(0.012)	(0.003)	(0.005)	(0.004)
Experience	-0.253**	-0.050	-0.058**	-0.009	-0.004	0.096	0.102
	(0.105)	(0.058)	(0.029)	(0.076)	(0.017)	(0.113)	(0.063)
ESeG	-0.028	-0.093**	-0.017**	0.049	0.011	0.103*	0.039
	(0.057)	(0.037)	(0.017)	(0.049)	(0.011)	(0.053)	(0.033)
Permanent contract	-0.264***	-0.075	-0.134***	-0.147*	-0.036*	-0.042	0.028
	(0.083)	(0.051)	(0.041)	(0.078)	(0.021)	(0.100)	(0.062)

Table 7 (continued)

Variables	Hungary (2010–2019)			Slovakia (2010–2019)		Bulgaria (2010–2019)	
	90–10	50–10	Gini	90–10	Gini	90–10	50–10
Supervisory	0.0005	-0.005	-0.005	0.026**	0.002	0.017	-0.005
	(0.018)	(0.007)	(0.005)	(0.012)	(0.003)	(0.018)	(0.006)
Sector	-0.013	-0.017	0.008	0.010	-0.0003	-0.025	0.016
	(0.085)	(0.054)	(0.020)	(0.066)	(0.012)	(0.079)	(0.045)
Constant	0.590***	0.515***	0.168***	-0.082	0.063	0.067	0.096
	(0.172)	(0.110)	(0.049)	(0.180)	(0.064)	(0.177)	(0.111)
Reweighting error	-0.0001	-0.001	0.0003	0.002	0.001	0.002	0.001
	(0.010)	(0.005)	(0.003)	(0.006)	(0.001)	(0.013)	(0.006)

Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Authors' calculation based on EU-SILC (Eurostat) data

increasing their wages due to the minimum wage. Consequently, there is a possibility of underestimating the influence of the minimum wage on inequality change in Hungary, and a definitive answer to this issue would require additional research.

The estimations in Tables 5 and 7 depict a nuanced scenario in Slovakia. When controlling for shifts in the minimum wage, it becomes evident that composition effects play a more prominent role, while the wage structural effects are statistically insignificant for both the 90–10 log wage gap and the Gini index. Despite this, the marginal effects of individual variables in the compositional change—such as workers with permanent employment contracts, those with supervisory responsibilities, and married individuals—remain relatively consistent. However, there is a shift in significance, with the sector's contribution now emerging as significant for both the 90–10 log wage gap and the Gini index. While the estimated constant in the 90–10 log wage gap loses significance and becomes less influential in the decomposition with a constant minimum wage, there is a notable shift in the wage structure effect: the return to permanent employment contracts becomes a statistically significant and influential factor for both the 90–10 log wage gap and the Gini index. These findings collectively indicate that no definitive evidence suggests that changes in the minimum wage in Slovakia directly influence the shift in the 90–10 log wage gap and the Gini index.

In Bulgaria, the estimated constants lose significance in both the 90–10 and 50–10 log wage gaps after accounting for the change in the minimum wage (Table 7). While the marginal effects of individual variables (the return to education and socioeconomic groups) explaining the structural effect experience a slight increase, they do not lose their significance. Specifically, regardless of the characteristics of both workers and firms, the estimated constant decreased and became statistically insignificant. This outcome supports the hypothesis that change in the minimum wage impacts on changes in both the 90–10 and 50–10 log wage gaps.

Overall, the wage adjustment process in these countries may experience spillover effects due to the raised minimum wage; consequently, the estimates of the minimum wage's influence on inequality change may be subject to some bias (Teulings 2003). This bias may be seen entirely or partially in the residual part of the inequality change explained by the change in the estimated constant. A solid response to this topic necessitates extensive research beyond this paper's scope.

6 Conclusion

This article examines the drivers of wage inequality and its changes in six CEE countries over the last decade. We focus on the micro-level determinants and the minimum wage changes and estimate their effects using RIF regression and decomposition models for several inequality measures, including the Gini index and the log wage gaps (90–10, 90–50, and 50–10).

The wage inequality in the selected countries diverged more in 2019 than in 2010 – particularly since 2013, owing to different wage increases throughout the distribution. Mean hourly wage growth at the bottom of the wage distribution outpaced that of the top in Poland and Slovakia, narrowing wage disparities. Mean hourly wage growth in Czechia and Romania is distributed evenly across all wage percentiles, resulting in no discernible change in wage inequality. Wage disparities have recently expanded in Bulgaria and Hungary as the wage gap between those at the bottom of the wage distribution has widened.

In terms of shedding light on the demographic and micro-level determinants of wage inequality changes, among demographic and human capital characteristics, female gender, upper secondary school education, and permanent employment contracts have a diminishing impact on all measures of wage inequality. Upper secondary school education and a permanent employment contract are essential determinants in reducing wage inequality in all selected countries, with female participation being more crucial in Hungary, Poland, and Bulgaria. In contrast, supervisory responsibilities positively affect wage inequality measures across all countries, while worker health difficulties positively impact wage inequality measures in some countries. Worker health difficulty has a much more significant effect on all wage gap measures in Czechia than in other countries, particularly at the bottom of the wage distribution. Higher education and marriage have different implications for wage inequality in different nations. They have an increasing effect in some nations, a diminishing effect in others, and a differential influence on the upper and lower ends of the wage distribution.

Concerning socio-economic groups, a general pattern is observed in the selected countries despite slight differences. Managers have a more pronounced impact on the upper tail of the wage distribution, whereas professionals, technicians, and associated professionals significantly influence the middle of the wage distribution. Meanwhile, clerks, service, and industrial employees significantly affect the lower tail of the wage distribution. Sectors diminish all measures of wage disparities in the selected countries (except the agriculture sector in Poland), with a greater impact at the bottom of the distribution. Regarding the sector, we have observed a similar pattern across the selected countries. The high-skill service sector exhibits a more pronounced impact on the upper tail of the wage distribution, while the low-skill sector has the most substantial impact in the middle. Conversely, the impacts of agriculture, construction, and public service on wage levels and inequality vary across countries.

This study decomposed the micro determinants of wage inequality changes into wage structure and composition impacts to investigate the causes of diverging movements in wage disparity in the selected nations. The changes in wage inequality were mostly driven by wage structure effects (returns to observed characteristics) regardless of the increase or decrease in wage inequality. In most countries, wage structure impacts are greatest at the bottom of the wage distribution, consistent with earlier research, including CEE countries (Magda et al. 2021; Pereira & Galego 2019). This trend, however, varies from the U-shaped wage structure impacts found in the United States by Firpo et al. (2018).

Regarding the determinants driving these inequality movements, some reduce while others increase wage inequality, and others increase or decrease disparity. Changes in the returns to education and returns to permanent employment contracts are crucial in explaining decreased wage inequality. We found falling returns to education at the 90–10 and 50–10 wage gaps and the Gini index, accompanied by rising educational attainment levels among workers in Poland. The increases in wage inequality in Hungary and Bulgaria are explained mainly by the changes in the estimated constants instead of micro-level determinants. The changes in the minimum wage explain most of the unknown factors in Bulgaria, and the spillover effects of the minimum wage may explain some of the unknown factors in Hungary. The role of minimum wage changes in Hungary is consistent with the previous findings of Pereira & Galego (2019). Examining the spillover effects of minimum wages on wage inequality is beyond the scope of this paper, and further research on this topic would be beneficial.

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Author contributions Both authors contributed to the conception and design of the study. Galambosné Dr. Tiszberger Mónika was in charge of acquiring EU-SILC data. Byambasuren Dorjnyambuu conducted data cleaning and analysis. The manuscript was written and revised by both authors. The final manuscript was read and approved by all authors. Galambosné Dr. Tiszberger Mónika oversaw the entire study.

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Data availability Due to Eurostat's confidentiality considerations, the datasets used in this study are not publicly available, although Eurostat permits access to microdata for scientific reasons in accordance with Regulation (EU) No 557/2013 on access to confidential data for scientific purposes.

(https://ec.europa.eu/eurostat/documents/203647/771732/How_to_apply_for_microdata_access.pdf).

Declarations

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