Research Article

Is University Education Worth It? Minimum Wage, Labor Supply Composition and Skill-Based Wage Gap in Türkiye: 2004-2023 Period

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Abstract: This study analyzes the effect of minimum wage changes and the proportion of skilled labor in the employment on the skill-based wage gap in Türkiye. We utilize Household Labor Force Survey (HLFS) micro data sets, covering the period from 2004 to 2023. We first analyze wage disparities between skilled and unskilled groups through a Heckman-type wage equation that accounts for sample selection. Subsequently, we compute the skill-based wage gap for each year using the Blinder-Oaxaca method. Finally, we apply an econometric model where the wage gap, derived from the microdata, serves as the dependent variable. Explanatory variables are the proportion of skilled labor in employment (calculated from the microdata) and real minimum wage changes, adjusted for inflation by deflating the average annual nominal increase. This methodology allows us to explore the issue from a broader macroeconomic perspective. The results from the Heckman wage equations reveal significant differences in the effect of factors on wage determination and job-finding probabilities between skilled and unskilled employees. The econometric analysis, which examines the overall factors influencing the skill-based wage gap, reveals that a 1% rise in the minimum wage leads to a 0.15% decrease in the wage gap. Additionally, a 1% increase in the proportion of skilled workers in the workforce results in a 0.26% reduction in the wage gap. These results suggest that the wage advantage tied to education is gradually decreasing, potentially leading to a future drop in the demand for university degrees.

Keywords: Minimum Wage, Heckman Sample Selection, Blinder-Oaxaca Decomposition, Survey Data Analysis
Jel Codes: J38, J31, J24, C55, C83

Üniversite Eğitimi Almaya Değer mi? Türkiye'de Asgari Ücret, İşgücü Arzı Kompozisyonu ve Beceri Temelli Ücret Farkı: 2004-2023 Dönemi

Öz: Bu makale, asgari ücret değişikliklerinin ve işgücündeki nitelikli iş gücünün oranının Türkiye'deki beceri temelli ücret farkı üzerindeki etkisini analiz etmektedir. 2004-2023 dönemi arasını kapsayan Hanehalkı İşgücü Anketi (HİA) mikro veri setleri kullanılmıştır. İlk olarak, becerili ve becerisi düşük gruplar arasındaki ücret farklılıkları, örneklem seçim hatasını dikkate alan Heckman tipi bir ücret denklemi ile analiz edilmiştir. Ardından, Blinder-Oaxaca ayrıştırma tekniği kullanılarak her yıl için beceri temelli ücret farkı hesaplanmıştır. Son olarak, mikro verilerden türetilen ücret farkının bağımlı değişken olarak kullanıldığı ekonometrik model oluşturulmuştur. Bağımsız değişkenler, işgücündeki nitelikli iş gücünün oranı (mikro verilerden hesaplanmış) ve enflasyona göre düzeltilmiş gerçek asgari ücret değişiklikleridir. Bu metodoloji, konuyu daha geniş bir makroekonomik perspektiften incelememize olanak tanımaktadır. Heckman ücret denklemlerinden elde edilen sonuçlar, becerili ve becerisi düşük çalışanlar arasındaki ücret belirleme faktörleri ve iş bulma olasılıkları üzerinde önemli farklılıklar olduğunu ortaya koymaktadır. Beceri temelli ücret farkını etkileyen genel faktörleri inceleyen ekonometrik analiz, asgari ücretteki %1'lik bir artışın ücret farkını %0,15 oranında azalttığını göstermektedir. Ayrıca, iş gücündeki nitelikli işçilerin oranındaki %1'lik bir artış, ücret farkını %0,26 oranında azaltmaktadır. Bu sonuçlar, eğitimle bağlantılı olan ücret avantajının giderek azaldığını ve bu durumun gelecekte üniversite diplomalarına olan talebin düşmesine yol açabileceğini göstermektedir.

Anahtar Kelimeler: Asgari Ücret, Heckman Örneklem Seçimi, Blinder-Oaxaca Ayrıştırması, Anket Verisi Analizi
Jel Kodları: J38, J31, J24, C55, C83

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1. Introduction

Human capital refers to the abilities, expertise, and knowledge that people develop over the course of their lives. Investment in human capital—especially through education, which is the main focus of this paper—is thought to nurture a more educated and skilled workforce, ultimately boosting productivity. Employees with higher levels of skills and knowledge tend to be more productive and proficient in their tasks, leading to increased output. Consequently, education plays a crucial role in driving economic growth, promoting innovation, and supporting societal progress.

Human capital theory posits a robust link between education and the enhancement of human capital: that is, investing in education directly improves the skills and capabilities of the workforce. Firstly, as mentioned earlier, education provides individuals with essential skills and knowledge that improve their productivity. Consequently, higher levels of education are typically linked to a more skilled and capable workforce. Second, educated individuals enjoy better access to employment opportunities. Employers often prioritize candidates with higher educational qualifications, which in turn increases the employment prospects for those with greater educational attainment. Third, education offers benefits that go beyond the economic realm, bringing substantial social advantages, including better health outcomes, reduced crime rates, and greater civic participation—factors that together enhance the overall quality of life in communities.

Additionally, human capital theory highlights the significance of lifelong learning and the ongoing improvement of skills. In a time of fast technological progress and changing labor market needs, continuous education helps individuals adjust to emerging challenges, stay competitive in their careers, and fulfill the evolving demands of their jobs.

Moreover, investment in education is strongly correlated with higher earnings. There is broad consensus in labor economics that people with advanced levels of education typically receive considerably higher salaries (Becker, 1964; Mincer, 1974). This growing wage disparity between the most skilled and the least skilled workers—essentially the "price" for human capital—drives much of the widening income inequality. The Skill-Biased Technical Change (SBTC) hypothesis asserts that technical advancements primarily favor skilled workers, increasing the need for skilled labor while decreasing the demand for unskilled labor. This shift results in greater wage inequality between these two groups. The underlying theory suggests that as technology evolves, it increasingly requires more advanced skills and education. In essence, technological innovations, particularly in computing, are complementary to human capital. As firms adopt new technologies, they seek workers who possess the expertise to leverage these tools effectively. Consequently, the rising demand for skilled workers, coupled with a relatively fixed supply, drives up wages for those with the requisite skills, thereby exacerbating income inequality.

The shifts in wage inequality have been examined in terms of the underlying forces driving these changes. One significant factor frequently discussed is the evolution of labor market institutions, particularly adjustments to the real minimum wage. These adjustments are often cited as a crucial explanation for changes in inequality, given that minimum wage policies are specifically designed to improve the welfare of low-skilled workers (DiNardo, Fortin, & Lemieux, 1996; Card & DiNardo, 2002; Lee, 1999).

The main purpose of a minimum wage is to set a base at the bottom of the income scale. Changes to the minimum wage can influence inequality through multiple channels. On one hand, increased minimum wage provides a more even distribution in the lower end of the distribution, where a substantial proportion of minimum wage earners are concentrated. Minimum wage hikes result in substantial real wage gains for workers in the bottom half of distribution, thereby narrowing the gap between them and those in the upper half. This phenomenon, often referred to as wage compression, occurs when wages for low-skilled jobs rise significantly, while wage growth for higher-skilled workers may not increase at the same rate. Furthermore, in the long term, the skill premium incentivizes low-skilled workers to acquire the necessary skills through formal education and on-the-job training. As the number of skilled workers increases, the skill premium tends to decrease because of the rising share of skilled labor. Consequently, the observed wage differential between skilled and unskilled individuals is likely to shrink, as the basement wage for the bottom half of the income distribution rises.

For the purposes of this research, employees with at most a high school diploma are counted as unskilled and the rest are classified as skilled. As shown in Table 1, the proportion of skilled employees has steadily increased across all sectors throughout the analyzed period. Alongside the rise in the share of skilled workers, the wage gap gradually narrowed. For example, in 2005, the mean wage of skilled workers in the trade sector was 2.31 times that of unskilled workers, but by 2023, this ratio had decreased to 1.35. This trend is consistent across all sectors over the period analyzed.[1].

Table 1. Distribution of unskilled and skilled workers over sectors and average wages (in TL) for selected years.

	2005		**2014**		**2023**	
Sector	**UnSkilled**	**Skilled**	**UnSkilled**	**Skilled**	**UnSkilled**	**Skilled**
Industry-Average Wage	413	929	1160	2311	11736	19317
Frequency	92.83	7.17	88.04	11.96	80.89	19.11
Construction-Average Wage	314	685	1229	2573	11527	17172
Frequency	93.21	6.79	89.57	10.43	84.33	15.67
Trade-Average Wage	203	469	1115	1833	10804	14609
Frequency	90.83	9.17	85.37	14.63	75.82	24.18
Services-Average Wage	426	897	1239	2635	11258	21356
Frequency	72.03	27.97	61.30	38.70	53.56	46.44
Total	87.64	12.36	79.89	20.11	70.54	29.46

Source: Author's own calculation over HLFS micro datasets.

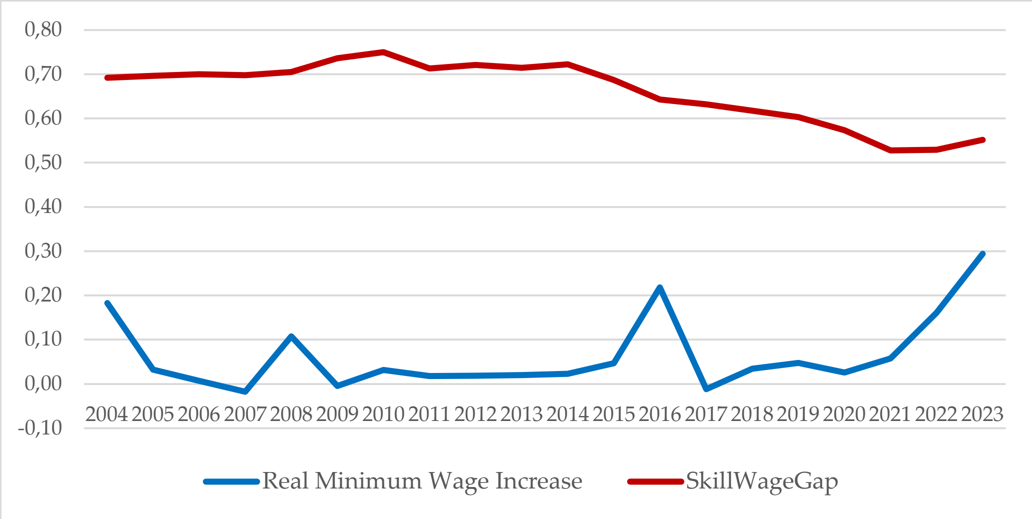
Furthermore, as the minimum wage increases, the ratio of mean wages between highly educated individuals and those earning the minimum wage tends to shrink over time. This shift may result in alterations to the educational or skill makeup of the workforce. A decline in the returns to education, manifesting as lower wages for highly skilled workers, reduces the incentives for individuals to pursue higher education, as they base their educational choices on anticipated employment prospects and income. Consequently, this reduction in the perceived value of higher education may lead to a decline in educational attainment at the upper end of the distribution of wages.

On the demand side, an increase in minimum wages likely elevates employers' labor costs. Moreover, in most sectors and companies, the proportion of low-skilled workers significantly exceeds that of skilled employees, leading to a substantial rise in overall labor costs when minimum wages are raised. As a result, firms often mitigate the impact of higher wages for the majority of their workforce by constraining wage increases for skilled employees. Figure 1 below illustrates the real increase in minimum wage and the skill-based wage gap from 2004 to 2023. As shown, the real minimum wage consistently rose throughout this period, with notable peaks in 2008, 2016, and 2023, indicating an increase in the real income of minimum wage earners. In contrast to the rise in minimum wages, the skill-based wage gap has narrowed, reflecting the mechanisms discussed earlier. Skill-

[1] Since six zeros were removed from the Turkish Lira in 2005, 2005 was chosen as the first year of the sectoral distribution and average wage table and 2014 and 2023 are chosen as the other years to illustrate the trend. Average wages and sectoral distribution of skilled and unskilled employees is computed for all years and they are available upon request.

based wage gap is computed over the given period with Blinder-Oaxaca decomposition method by using the micro data sets of Household Labor Force Survey (HLFS).

Figure 1. The real minimum wage increases and skil- based wage gap in Türkiye (2004-2023)



Source: The real increase in minimum wages is computed by author over the nominal minimum wage data of Ministry of Labor and Social Security. The average minimum wage was considered for years with multiple adjustments, and all wage levels were adjusted using the 12-month Consumer Price Index for December of each year to ensure consistency.

Wage disparities arise not only from differences in employee endowments but also from the varying ways these endowments are priced in job market. In the analytical section (Section 3) of this research, we first examine the wage structures of skilled and unskilled workers using a Heckman wage equation with selection. These wage equations are estimated using microdata from the HLFS for the period 2004-2023. This approach allows us to empirically demonstrate that the endowments and wage-determining factors for the two groups are differently priced in the labor market. Next, we calculate the skill-based wage gap using the Blinder-Oaxaca method, once again leveraging the HLFS microdata. Finally, we develop an aggregate model to explore the dynamics of the skill-based gap during the analyzed period. In this model, we treat the wage gap as the dependent variable, while the labor share of skilled labor and real minimum wage increases serve as independent variables in an OLS regression framework.

Thus, the following section reviews the related literature. Section 3 explains data and methodology, 4th section presents the empirical findings and the last section is conclusion.

2. Related Literature

The literature examining educational wage disparities is extensive and varied. One prominent strand of research emphasizes impact of technological progress in explaining the widening wage gap. Studies in this tradition argue that Skill-Biased Technical Change (SBTC), as discussed earlier, is a key driver of rising inequality. Empirical evidence from scholars such as Katz & Murphy (1992), Juhn, Murphy & Pierce (1993), and Autor, Katz & Kearney (2008) supports this view, demonstrating that the increased demand for high-skilled labor, coupled with the growing supply of skilled workers due to technological advancements, accounts for the rising skill premiums.

In contrast, another body of literature, beginning with the work of DiNardo, Fortin & Lemieux (1996), highlights the importance of institutional factors—such as unionization and minimum wage policies—in clarifying wage disparity. Their decomposition analysis suggests that the erosion of labor market institutions, particularly de-unionization and the decline of real minimum wages, plays a role as significant as supply and demand factors in exacerbating inequality in the United States. These findings imply that labor market institutions should be considered alongside changes in labor supply and demand when assessing wage inequality. Lee (1999) further corroborates this perspective, demonstrating that much of the widening wage variation at the bottom of the distribution can be attributed to fluctuations in minimum wage levels. His analysis suggests that, had the minimum wage remained steady during the analyzed period, wage inequality at the bottom would have been much lower. Later, Autor, Manning & Smith (2016) extend this line of inquiry, finding that while minimum wages do reduce inequality in the U.S., the effect is smaller than previously thought. They also show that increases in the minimum wage have spillover effects, affecting segments of the wage distribution that are not directly targeted by the policy.

Sutch (2010) investigates the long-term effect of minimum wage adjustments on educational enrollments in the U.S. between 1950 and 2003, suggesting that the cumulative impacts of minimum wage policies have triggered a cascade of educational decisions. This implies that changes in wage structure, particularly at the lower end, influence individuals' incentives to pursue further education. Additionally, studies from European countries show that the impact of labor market institutions and policies can vary significantly by context. Research by Machin (1997) and Dickens, Machin & Manning (1999) indicates that in the UK, larger union representation and stronger minimum wage protections have helped mitigate wage inequality. Crivellaro (2014) finds that, despite rising demand for skilled workers, Europe's more regulated and compressed labor markets have played a role in decreasing educational wage inequality, further suggesting that institutional factors can shape the wage distribution in diverse ways across different national contexts.

There is a substantial body of literature examining education-related wage inequality within the Turkish labor market. Vural & Gülcan (2008) estimate the returns to education using data from the Household Budget Survey (HBS) for 1994 and 2004. Their findings highlight that the returns to education vary across different sectors of the economy and serve as a key driver of wage dispersion. Tansel & Bircan-Bodur (2012) apply quantile regression techniques to analyze the development of male wage disparity in Türkiye between 1994 and 2002, also using HBS data. They demonstrate that education has exacerbated wage inequality, both within groups and across different demographic categories. Mocan (2014) evaluates the impact of the 1997 education reform on labor market outcomes by analyzing the 2011 and 2012 Household Labor Force Surveys (HLFS). The study finds a significant increase of over 20 percentage points in the proportion of children completing middle school as a result of the reform. Bakis & Polat (2015) analyze wage inequality in Turkey from 2002 to 2010, using HLFS data. They observe a significant rise in the number of college-educated workers compared to those with lower levels of education, which resulted in a decrease in the relative wages of the highly educated during this time. Their decomposition of wage inequality suggests that changes in education premium, rather than shifts in the educational composition of the workforce, largely explain the observed trends. The authors attribute this decline in inequality to institutional changes, particularly the sharp rise in the minimum wage. Popli & Yılmaz (2017), also using HLFS data, argue that decreased wage inequality may be linked to the diminishing value of unmeasured skills. They further contend that significant quality differences in higher education could explain variations in wage differentials. Their analysis of occupational task measures reveals that they play a role in contributing to wage inequality in Turkey. In a related study, Caner, Demirel-Derebasoglu & Okten (2022) investigate the causal effects of Turkey’s large-scale expansion of higher education on the college wage premium. They find that the rapid growth in university enrollments, including the establishment of new institutions, contributed to a reduction in the college wage premium, particularly among young men. Karakülah (2024) focuses on the 1997 education reform’s impact on earnings, finding that people born after 1986, who gained from the reform, saw increased returns on their education, leading to higher earnings than individuals born prior to 1986 with similar levels of education and experience. This effect was more significant for women than for men.

The literature on the relationship between minimum wage policy and wage inequality is more limited. Bakis, Hisarciklilar & Filiztekin (2015) analyze the 2004 minimum wage increase using HBS data and find that the rise in the minimum wage had a dual impact: it reduced teenage employment while encouraging school enrollment. Bakis & Polat (2015), discussed earlier, also attribute the decline in wage inequality from 2002 to 2010 to institutional changes, particularly the substantial minimum wage increases during this period. They show that the real increase in the minimum wage in 2004 was a key factor in narrowing the wage gap between the highest and lowest earners, as measured by the 90/10 and 50/10 wage percentiles. Pelek (2018) explores the broader effects of the 2004 minimum wage increase on wage inequality, with a focus on gender. Her analysis indicates that the policy significantly reduced wage inequality for both male and female workers between 2003 and 2005. Işık, Orhangazi & Tekgüç (2020) also study the effects of the minimum wage increase, finding that while it had no significant impact on employment, it did lead to substantial wage increases, particularly among higher-educated workers. Bakis & Polat (2023), using HLFS data from 2002 to 2019, further corroborate the finding of a significant decline in wage inequality. Their research examines the impact of two major policy measures: increases in the minimum wage and the expansion of education. They conclude that the two minimum wage hikes during this period resulted in lasting real gains for lower-wage earners and contributed to a narrowing of the wage gap across percentiles. Their decomposition analysis shows that these increases had a major impact on the overall distribution of wages.

Building on this body of research, this study seeks to explore the effects of minimum wage increases on the educational wage gap in Turkey. The minimum wage policy is likely to have a significant impact on wage dynamics, as more than half of the country's wage earners are heavily dependent on the minimum wage.

3. Data and Methodology

Data

We draw on individual-level data from the annual microdata sets of the Household Labor Force Survey (HLFS), provided by the Turkish Statistical Institute (TurkStat) for the period from 2004 to 2024. The HLFS is the primary source of labor market statistics in Turkey, offering detailed demographic and socio-economic information about the entire labor force, including both formal and informal workers. The dataset includes variables such as age, gender, education, marital status, employment status, job type, hours worked, income from paid employment, and duration of unemployment. Through sampling and weighting methods, the data is standardized to accurately represent Turkey’s non-institutional population. The survey follows a repeated cross-sectional design. For our analysis, we focus on individuals aged 14 and older who are active in the labor force. We exclude data from the economic crisis years of 2000-2001 and the subsequent recovery period (2002 and 2003) for two reasons: first, significant increases in the real minimum wage began only in 2004, and second, the 2003 survey lacked a question on employment type. Minimum wage data is sourced from the Ministry of Labor and Social Security.

Table 2 presents the distribution of unskilled and skilled workers across various dimensions, including sector, gender, employment type and firm size. In terms of sectoral distribution, trade stands out as the sector with the highest proportion of skilled employees, while agriculture, as expected, has the largest share of unskilled workers. However, across all sectors, the proportion of skilled employees has risen over the analyzed period.

The ratio of skilled employees is higher among women than men, highlighting that the effect of education on employment opportunities is more pronounced for women.

Over the analyzed period, the proportion of skilled workers has increased for both genders.

Table 2 reveals that as firm size grows the share of skilled employees also rises. This is likely due to larger firms being more capital-intensive, which necessitates a workforce with higher skill levels. Additionally, Table 2 shows that the share of skilled workers is higher in registered employment compared to unregistered employment. This is consistent with expectations, as individuals with lower levels of education are more likely to be employed in informal sectors. The same fact holds for part-time full-time employment division. As expected, the share of skilled employees is higher in full time employment.

Table 2. Distribution of unskilled and skilled workers

	2004		2014		2023	
Dimension	Unskilled	Skilled	Unskilled	Skilled	Unskilled	Skilled
Sector						
Agriculture	99.19	0.81	98.32	1.68	95.67	4.33
Industry	92.83	7.17	88.04	11.96	80.89	19.11
Construction	93.21	6.79	89.57	10.43	84.33	15.67
Trade	90.83	9.17	85.37	14.63	75.82	24.18
Services	72.03	27.97	61.30	38.70	53.56	46.44
Gender						
Female	84.00	16.00	75.44	24.56	63.44	36.56
Male	88.88	11.12	81.78	18.22	74.03	25.97
Firm Size						
1-9 Employees	95.06	4.94	---	----	83.89	16.11
1-10 Emp.	---	---	91.09	8.91	---	---
10-24 Emp.	80.61	19.39	---	---	---	----
11-19 Emp.	---	---	72.67	27.33	67.12	32.88
20-49 Emp.	---	---	68.07	31.93	58.66	41.34
25-49 Emp.	72.74	27.26	---	---	---	---
50+ Emp.	---	---	61.34	38.66	---	---
Unknown	---	---	83.89	16.11	70.71	29.29
50-249 Emp.	74.37	25.63	---	---	57.28	42.72
250-499 Emp.	77.78	22.22	---	---	---	---
250+ Emp.					51.99	48.01
500+ Emp.	74.69	25.31	---	---	---	---
Registered Employment						
Unregistered	97.44	2.56	96.72	3.28	92.62	7.38
Registered	78.53	21.47	71.39	28.61	63.32	36.68
Employment Type						
Full Time	87.40	12.60	78.38	21.62	69.47	30.53
Part-Time	91.81	8.19	91.70	8.30	80.73	19.27
Public / Private Employment						
Public	----	----	36.59	63.41	30.15	69.85
Private	----	----	86.79	13.21	78.18	21.82
Total	87.64	12.36	79.89	20.11	70.54	29.46

Source: Author's own calculations over HLFS micro data.

Table 3 presents the average wages of unskilled and skilled employees across the dimensions outlined in the previous table. The year 2005 was selected as the starting point for the wage data to conserve space, as six zeros were removed from the Turkish Lira at that year. First and foremost, Table 3 clearly demonstrates that the skill-based wage gap has narrowed over the analyzed period. In terms of sectoral differences, agriculture shows the largest wage gap. The ratio of skilled women's wages to those of unskilled women is higher than that of men, indicating a larger skill-based wage gap among women. However, this gap has steadily decreased for both genders throughout the period.

Regarding the impact of firm size on the skill-based wage gap, the data suggests that the gap tends to decrease as firm size increases. This trend could be interpreted as an indication of a more equitable wage distribution within larger firms. While the skill-based wage gap was initially higher at the start of the period, this pattern has since reversed. Additionally, because unregistered jobs are more likely to be low-quality or "nondecent" positions, one might expect a narrower skill gap in comparison to registered jobs. Interestingly, the data from the beginning of the analyzed period contradicts this expectation.

As expected, part-time jobs exhibit a wider skill-based wage gap than full-time positions. Additionally, the skill-based wage gap is narrower in the public sector than in the private sector.

Table 3. Average wages of unskilled and skilled employees over various categories

Average Wages	2005		2014		2023	
Dimension	Unskilled	Skilled	Unskilled	Skilled	Unskilled	Skilled
Sector						
Agriculture	120	331	825	2099	8562	16922
Industry	413	929	1160	2311	11736	19317
Construction	314	685	1229	2573	11527	17172
Trade	203	469	1115	1833	10804	14609
Services	426	897	1239	2635	11258	21357
Gender						
Female	187	486	950	2221	9243	18011
Male	282	641	1250	2714	12107	22002
Firm Size						
1-9 Employees	120	286	---	----	9023	13837
1-10 Emp.	---	---	1011	1813	---	---
10-24 Emp.	423	824	---	---	---	----
11-19 Emp.	---	---	1183	2287	11106	17399
20-49 Emp.	---	---	1219	2340	11830	19090
25-49 Emp.	497	873	---	---	---	---
50+ Emp.	---	---	1386	2878	---	---
Unkonown	---	---	1071	2025	12416	20025
50-249 Emp.	603	1086	---	---	12633	21109
250-499 Emp.	643	1260	---	---	---	---
250+ Emp.					14046	25392
500+ Emp.	755	1290	---	---	---	---
Registered Employment						
Unregistered	123	278	802	1167	6714	10083
Registered	419	890	1286	2558	12090	20465
Employment Type						
Full Time	273	836	1209	2543	11643	20526
Part-Time	40	640	475	2082	4642	15028
Public / Private Employment						
Public	----	----	1718	2771	15170	22674
Private	----	----	1117	2288	10831	18364
Total	202	581	1182	2525	11298	20275

Source: Author's own calculations over HLFS micro data.

Methodology

Turkey's labor supply and employment landscape show significant diversity, particularly in terms of gender and skill distributions within the workforce. While women make up half of the population, they represent only about a quarter of the labor force. Men, despite generally having lower educational levels, still participate in the workforce at higher rates. In contrast, the educational background has a far greater impact on women's labor force participation. In essence, as women attain higher levels of education, their likelihood of entering the workforce increases, whereas those with lower educational attainment are more likely to remain outside it. This results in a marked heterogeneity in both overall employment rates and the distribution of employment across different educational levels for both genders. Such uneven distribution challenges the assumption of normality in the estimation coefficients, leading to potentially unreliable predictions. To account for this heterogeneity, the study adopts the two-stage Heckman selection model, which is better suited for datasets with such characteristics.

Heckman (1979) argued that focusing only on individuals who are employed in order to assess the effects of variables like education and age on wages could introduce bias. This is particularly problematic when certain groups, such as women who choose not to work due to wages being lower than their reservation wages, or highly educated individuals who feel their qualifications aren't compensated adequately in the labor market, are excluded. The absence of high-skilled individuals—who may opt out of the labor force because they view the wage return on their education as insufficient—along with women staying out of the labor force for reasons such as family obligations, distorts the understanding of gender's effect on wages. Moreover, including less educated men while excluding women who are not employed for various reasons can further skew assessments of both gender and educational impacts on wages. In addition, this selective inclusion of certain individuals can bias other coefficients in the wage equation, as the sample might differ in other key explanatory variables from those excluded. To correct for these biases, Heckman proposed a two-stage model that adjusts for sample selection issues.

Assume that we are trying to estimate the following wage equation:

$$W_i = \vartheta X_i + \varepsilon_i \tag{1}$$

where W_i denotes the wage of individual i, X_i denotes the endowments vector of individual i, ϑ denotes the coefficients vector and ε_i is the error term.

The concept of reservation wage plays a critical role in determining an individual's decision to participate in the labor market. Essentially, a person sets a minimum acceptable wage for themselves, below which they will opt not to work. If the market wage aligns with their reservation wage, the individual will feel neutral about entering the workforce. On the other hand, if the market wage surpasses their reservation wage, they are more likely to decide to seek employment (E_i=1, where E indicates the decision to work or not). Although reservation wages of individuals are not observable, we can infer their labor force participation by whether they are employed or not. Thus, we assume that Ei=1 when an individual is working, indicating that they will only engage in the labor market if the wage offered exceeds their reservation wage. Therefore, we proceed with the assumption that:

$$E_i = \begin{cases} 1 \to enter\ workforce\ if\ W_i - R_i > 0 \\ 0 \to do\ not\ enter\ workforce\ if\ W_i - R_i < 0 \\ 0 \to indifferent\ if\ W_i - R_i = 0 \end{cases} \tag{2}$$

Now, we can define the status, or decision of an individual regarding the work force as:

$$E_i = \theta A_i + \varepsilon_i \tag{3}$$

In this framework, θ represents the vector of coefficients associated with observable individual characteristics, which include factors such as education, age, work experience, marital status, and other pertinent attributes, while A_i captures the specific characteristics of individual i. These attributes are instrumental in influencing an individual's decision to participate in the labor market. Consequently, the first stage of the Heckman two-step procedure entails the estimation of a probit model—similar to Equation 3—to account for potential sample selection bias. In the second stage, a standard wage equation, akin to Equation 1, is then estimated to assess the wage outcomes for those already in the labor force.

Given that the primary focus of this analysis is the skill-based wage gap, the empirical investigation begins with separate labor force participation regressions for skilled and unskilled workers. In this study, individuals possessing a university degree or higher are classified as skilled, while those with lower educational attainment are categorized as unskilled. The labor force participation equation, which functions as the "selection" equation within the Heckman framework, is specified as follows:

$$Emp_i = \theta_0 + \theta_1 Age_i + \theta_2 Age_i^2 + \theta_3 HouseholdSize_i + \theta_4 NumberOfIncomeEarners_i + DGender_i * MaritalStatus_i + \varepsilon_i \quad (4)$$

The dependent variable, *Emp*, takes a value of one if the individual is either employed or actively seeking employment, indicating participation in the labor force. Conversely, it equals zero when the individual is not part of the labor force. Variables such as age and experience are expected to have a positive, yet diminishing, effect on labor force participation. Accordingly, one would anticipate that $\theta_1>0$ and $\theta_2<0$. Specifically, the coefficient for age is expected to be higher for skilled workers, as unskilled individuals tend to have fewer opportunities for upward mobility and wage growth. Consequently, age and experience are anticipated to exert a more significant influence on wage increases for skilled workers compared to their unskilled counterparts.

As household size increases, the likelihood of labor force participation tends to decrease for both skilled and unskilled individuals, leading to the expectation that $\theta_3<0$ for both groups.

The impact of the number of income earners in a household on labor force participation varies according to the socioeconomic status of the family and the gender of the individual. In more traditional, lower-educated households—often populated by unskilled individuals—the probability of women entering the labor force typically declines if the husband is employed. However, due to lower household income, the necessity for additional income may counterbalance this effect, prompting women to seek employment. In contrast, for men, the number of income earners within a household generally does not have a significant effect on their participation in the labor force. Given these dynamics, the sign of θ_4 for unskilled individuals remains ambiguous.

For skilled individuals, however, the number of income earners is likely to have a positive influence on labor force participation. This is because the presence of multiple earners within a household can stimulate greater job search efforts among family members. Therefore, it is expected that θ_4 will be positive for skilled workers.

The variable “D” represents the coefficient for the interaction between marital status and gender dummy variables, with "single and female" serving as the reference category. Marriage tends to have a positive impact on labor force participation for men in both skilled and unskilled groups, primarily due to factors such as age, familial obligations, and traditional gender expectations. In contrast, marriage and/or childbearing often lead women, particularly those in unskilled positions, to exit the workforce. As a result, the marriage dummy variable is expected to have a positive coefficient for men but a negative one for women across both skilled and unskilled groups. The effect of widowhood, however, remains uncertain for both subgroups. While widowhood typically leads to a decrease in household income, prompting women to join the labor force, widows are often older, which may hinder their ability to actively seek employment.

Lastly, θ_0 represents the constant term, and ε_i denotes the error term.

Following the selection equation, the second stage of the Heckman model involves estimating the standard wage equation. The explicit form of this wage equation, as shown in Equation 1, is as follows:

$$LnWage_i = \alpha_0 + \alpha_1 Age_i + \alpha_2 Age_i^2 + D_1 Sector_i + D_2 Firmsize_i + D_3 EmploymentType_i + D_4 RegEmployment_i + D_5 PublicPrivate + D_6 Gender_i + \mu_i \quad (5)$$

The effects of age and its square term align with those observed in the selection equation, implying that α_1 expected to be positive, while α_2 should be negative. Larger firms are generally perceived as more capital-intensive, which, in turn, drives higher labor productivity and subsequently leads to increased wages as firm size grows. According to the Turkish Statistical Institute's surveys, firm size is categorized by employee count into the following groups: "1-9 employees," "10-49 employees," "50-249 employees," and "250+ employees." While this classification has evolved over the study period, the smallest category, "1-9 employees," is chosen as the reference group, with the expectation that wages will rise as firm size expands. As a result, the dummy variables for firm size are anticipated to yield positive coefficients.

Furthermore, the impact of firm size on wages is expected to be more pronounced for skilled workers. This is because skilled employees typically experience greater variability in job roles and pay levels across different firm sizes, whereas unskilled workers tend to engage in more standardized and less diverse tasks, irrespective of the size of the firm.

With respect to the sector dummies, agriculture—being the sector with the lowest wages—serves as the reference category. The dummies for the industry, construction, and services sectors are expected to have positive coefficients, reflecting higher wages in these sectors compared to agriculture. The EmploymentType variable distinguishes between part-time and full-time contracts, with full-time employees anticipated to receive higher wages across both skilled and unskilled groups. The RegEmployment variable indicates whether an individual's employment is registered or unregistered, with registered workers expected to earn more in both groups. Additionally, the PublicPrivate dummy differentiates between public sector employees (including those working in non-governmental organizations) and private sector employees, with public sector workers expected to earn higher average salaries in Türkiye. Finally, α_0 represents the constant term, and μ_i denotes the error term.

The Heckman wage regression model, accounting for sample selection bias, is applied to microdata from the Household Labor Force Survey for each year from 2004 to 2023. This analysis includes both skilled and unskilled workers and is conducted using Stata 17 statistical software.

The regression results are consistent with economic theory, showing that a substantial majority of the explanatory variables are statistically significant at the 1% level. The wage equation regression findings reveal that the factors influencing wages differ between skilled and unskilled workers in Turkey over the specified period. This variation highlights the presence of a skill-based wage gap at the microeconomic level. A detailed discussion of the regression results is provided in the results section.

After identifying the underlying causes of the skill-based wage gap through the Heckman wage equation regressions, the gap is quantified for each year using the Blinder-Oaxaca decomposition method in the second phase of the empirical analysis. The Blinder-Oaxaca approach offers a rigorous statistical framework for analyzing wage differentials and potential discrimination by breaking down the wage gap into two components: the explained and the unexplained (Blinder, 1973; Oaxaca, 1973). The *explained* component refers to differences attributed to observable factors such as age, experience, sector, employment type, and firm size, while the *unexplained* component reflects the wage disparity that remains after controlling for these factors, often interpreted as resulting from differing market valuations of identical endowments.

In line with established empirical practices, the natural logarithm of wages is used to adjust for inflation and to facilitate the analysis of the elasticities between the explained and explanatory variables. The results show that the raw wage differential was 69.21% in 2004, steadily increasing each year until reaching a peak of 75.03% in 2010. Although there is a general decline in the gap from 2010 to 2023, there are occasional increases in specific years. The wage gap for 2023 is calculated at 55.17%, suggesting an almost inverse U-shaped pattern in the evolution of the skill-based wage disparity.

In the final stage of the empirical analysis, an Ordinary Least Squares (OLS) regression model is constructed to examine the skill-based wage gap from a macroeconomic perspective. In this model, the wage gap serves as the dependent variable, while the independent variables include the changes in the minimum wage and the proportion of employment classified by skill level. Thus, the OLS regression model for analyzing the wage gap at the macroeconomic level is specified as follows:

$$SWG_t = \alpha_0 + \alpha_1 MWI_t + \alpha_2 SL_t + \varepsilon_t \quad (6)$$

In this context, SWG_t denotes the skill-based wage gap in year t, MWI_t represents the increase in the minimum wage during year t, and SL_t indicates the proportion of skilled workers in employment at that time. "ε" is the error term for year t. An increase in the minimum wage is expected to have a narrowing effect on the wage gap by compressing the wage distribution, thus we hypothesize that $\alpha_1<0$. Similarly, as the share of skilled workers in the labor force rises, the wage premium associated with higher education is likely to diminish. In other words, as the supply of skilled labor expands, the "price" of skilled labor—reflected in the wages of skilled individuals—is expected to decrease. Thus, we expect that $\alpha_2<0$

4. Results

Heckman Wage Equation with Selection Results

As stated in the introduction, the first step of the analytical framework in this study is to examine the differences in wage formation between skilled and unskilled employees using the Heckman wage equation with selection. In other words, we will demonstrate that the coefficients of independent variables significantly differ in the wage equations for skilled and unskilled employees.

Table 4 presents the results of the Heckman model wage equation with selection for the years 2004 and 2023. While this regression is conducted for all years between 2004 and 2023, only the results for selected years are shown here; results for other years are available upon request.

Column (1) in each regression displays the results of the sample selection step for both skilled and unskilled employee groups, where the probability of job finding (Emp) serves as the dependent variable. Column (2) shows the wage regression, with the logarithm of net wage (LnNetWage) as the dependent variable. The bottom rows provide information on the sample size and the number of selected observations from the first step of the Heckman regression. For example, the 2004 HLFS survey includes nearly 240,000 observations of individuals aged 14 and older with a diploma lower than a university degree (unskilled), from which 57,262 observations were selected. Similarly, the dataset for skilled individuals (those aged 14 and older with higher education) contains 15,941 observations, with 11,359 selected for the regression analysis.

One key observation is that age has a more pronounced effect on the job-finding process than on wage formation for both groups. Moreover, Table 4 reveals that while the effect of age on wage is stronger for unskilled workers, the effect of age on job-finding probability is more significant for skilled workers. The square of age is negative in both the job-finding and wage formation equations for both groups, as expected.

The variable for gender*marital status, treated as an interactive dummy in the job-finding equations, uses "single female" as the base category. Unexpectedly, the negative effect of being a married female on job finding is stronger for skilled workers throughout the period. This suggests that educated women are more likely to leave the labor market or not actively search for a job compared to their less-educated counterparts, a trend contrary to initial expectations. One possible explanation for this is that higher-educated women may be more inclined to care for their own children rather than hire external childcare. Another notable finding is that marriage has a stronger positive effect on job search for unskilled males. Additionally, the negative effect of household size and the positive effect of the number of income earners in the family on job-finding probability are more pronounced for the skilled group, a pattern that remains consistent over the study period.

As anticipated, larger firm size has a greater impact on wages for both groups. While the magnitude of the firm size coefficients is larger for unskilled workers in some years, in other years, the reverse is true. Therefore, this relationship remains inconclusive.

Regarding employment type and status, the positive effect of registered employment on wages is more pronounced for skilled individuals, while the negative effect of part-time employment on wages is stronger for unskilled workers. This trend holds consistently across the entire analyzed period.

Finally, it is important to note that after 2008, labor force surveys introduced a public/private sector division. The regression results indicate that being employed in the public sector has a stronger positive effect on wages for unskilled workers.

Table 4. Heckman Wage Regression with sample selection

2004 Heckman Wage Regression with Selection	**Unskilled Employees**		**Skilled Employees**	
	(1)	(2)	(1)	(2)
VARIABLES	Emp	LnNetWage	Emp	LnNetWage
Demographic				
age	0.272***	0.0436***	0.317***	0.0308*
ageSquare	-0.004***	-0.0005***	-0.004***	-0.0002
Male		0.132***		0.0149
Firm Size				
10-24Employees		0.172***		0.215***
25-49Employees		0.225***		0.198***
50+		0.318***		0.305***
Sector				
Industry		0.267***		0.270***
Construction		0.321***		0.373***
Trade		0.342***		0.244***
Services		0.396***		0.280***
Employment Characteristics				
PartTime		-0.685***		-0.124***
RegisteredEmp		0.295***		0.463***
Gender*MaritalStatus				
Female*Married	-0.938***		-1.033***	
Female*Divorced	0.269***		0.0644	
Female*Widowed	-0.014		-0.288*	
Male*Single	0.700***		0.0812	
Male*Married	1.997***		1.052***	
Male*Divorced	1.269***		0.408**	
Male*Widowed	1.849***		0.405*	
Family Characteristics				
HouseholdSize	-0.240***		-0.359***	
NumberOfIncomeEarners	0.912***		1.585***	
athrho	-0.158***		-0.747***	
lnsigma	-0.635***		-0.510***	
Constant	-5.154***	18.15***	-5.227***	18.69***
Observations	238,039	238,039	15,941	15,941
Selected Observations	**57,262**	**57,262**	**11,359**	**11,359**
*** p<0.01, ** p<0.05, * p<0.1				

2023 Heckman Wage Regression with Selection	**Unskilled Employees**		**Skilled Employees**	
	(1)	(2)	(1)	(2)
VARIABLES	Emp	LnNetWage	Emp	LnNetWage
Demographic				
age	0.200***	0.032***	0.290***	0.045***
ageSquare	-0.003***	-0.0004***	-0.004***	-0.0004***
Male		0.139***		0.110***
Firm Size				
11-19Employees		0.121***		0.144***
20-49Employees		0.135***		0.198***
50-249		0.163***		0.283***
250+		0.243***		0.418***
Unknown		0.202***		0.189**
Sector				
Industry		0.0130		0.00237
Construction		0.0603***		-0.0106
Trade		0.075***		-0.014
Services		0.005		0.086*
Employment Characteristics				
PartTime		-0.879***		-0.347***
RegisteredEmp		0.402***		0.535***
Public		0.194***		0.155***
Gender*MaritalStatus				
Female*Married	-0.315***		-0.804***	
Female*Divorced	0.532***		0.220***	
Female*Widowed	0.252***		-0.237***	
Male*Single	0.742***		0.413***	
Male*Married	1.587***		1.082***	
Male*Divorced	1.153***		0.371***	
Male*Widowed	1.063***		1.056***	
Family Characteristics				
HouseholdSize	-0.229***		-0.448***	
NumberOfIncomeEarners	0.871***		1.580***	
athrho			-0.218***	
lnsigma			-0.704***	
Constant	-4.259***	8.232***	-5.154***	7.931***
Observations	298,207	298,207	69,432	69,432
Selected Observations	**86,628**	**86,628**	**49,191**	**49,191**
*** p<0.01, ** p<0.05, * p<0.1				

Source: Author's own calculations over HLFS 2004 and 2023 micro data.

Blinder Oaxaca Skilled Wage Gap Results

In the second step of the empirical analysis, we calculate the skill-based wage gap over the period using the Blinder-Oaxaca decomposition method applied to the micro datasets. This method decomposes the wage differential into explained and unexplained components, based on the explanatory variables. Table 5 presents the computed skill-based wage gap for selected years, with results for other years available upon request. The skill-based wage gap begins at 69% in 2004, reaches a peak of 75% in 2010, and then gradually narrows to 52% by 2021. From 2021 to 2023, the gap slightly increases, reaching 55%. Therefore, it can be concluded that the skill-based wage gap has generally decreased over the analyzed period. In other words, the education or skill premium on wages is continuously decreasing in Turkey in last 14 years.

Table 5. Blinder-Oaxaca skill-based wage gap decomposition for selected years.

2004 Results: 1: skilled = 0, 2: skilled=1, Number of obs = 68,621						
LnNetWage	Coefficient	Std. error	Z value	P>z	5%confidenceInterval	
Differential						
Prediction_1	19.738	0.000	91000.000	0.000	19.737	19.738
Prediction_2	20.430	0.000	42000.000	0.000	20.429	20.431
Difference	-0.692	0.001	-1308.050	0.000	-0.693	-0.691
Decomposition						
Endowments	-0.273	0.001	-316.270	0.000	-0.275	-0.271
Coefficients	-0.463	0.001	-870.520	0.000	-0.464	-0.462
Interaction	0.044	0.001	50.840	0.000	0.042	0.046
2014 Results: 1: skilled = 0, 2: skilled=1, Number of obs = 95,771						
LnNetWage	Coefficient	Std. error	Z value	P>z	95%confidence Interval	
Differential						
Prediction_1	6.955	0.000	46000.000	0.000	6.954	6.955
Prediction_2	7.677	0.000	29000.000	0.000	7.677	7.678
Difference	-0.723	0.000	-2371.630	0.000	-0.723	-0.722
Decomposition						
Endowments	-0.260	0.000	-655.620	0.000	-0.260	-0.259
Coefficients	-0.522	0.000	-1669.520	0.000	-0.523	-0.521
Interaction	0.059	0.000	148.070	0.000	0.058	0.060
2023 Results: 1: skilled = 0, 2: skilled=1, Number of obs = 135,819						
LnNetWage	Coefficient	Std. error	Z value	P>z	95%confidence Interval	
Prediction_1	9.197	0.000	59000.00	0.000	9.196	9.197
Prediction_2	9.748	0.000	46000.00	0.000	9.748	9.749
Difference	-0.552	0.000	-2105.990	0.000	-0.552	-0.551
Decomposition						
Endowments	-0.201	0.000	-686.910	0.000	-0.201	-0.200
Coefficients	-0.410	0.000	-1503.290	0.000	-0.411	-0.409
Interaction	0.059	0.000	195.380	0.000	0.059	0.060

Source: Author's own calculations over HLFS 2004 and 2023 micro data.

Aggregate OLS Regression Results

The aggregate model for the skilled wage gap, as defined in Equation 6 above, is regressed using the dataset constructed for this analysis. The dependent variable is the skilled wage gap, with observations derived from the Blinder-Oaxaca decomposition. The first explanatory variable is the real rate of increase in the minimum wage, computed by deflating the nominal annual increase by the Consumer Price Index (CPI) of December each year. The second explanatory variable is the share of skilled labor in total employment, calculated using microdata from the HLFS. Table 6 presents the results of the aggregate regression. Both explanatory variables and the constant term are found to be significant at the 5% level. Table 7 represents the summary statistics for the OLS model.

Based on these findings, we conclude that the skill-based wage gap has decreased primarily due to two factors. First, the expansion of the skilled labor force, driven by supply and price mechanisms, has contributed to a reduction in the skill premium. In other words, as the share of skilled labor in the workforce increased, the relative wage premium for skilled workers declined over the period. Second, as the minimum wage rose in real terms, firms faced higher labor costs, which likely constrained their ability to increase skilled workers' wages at the same rate, further contributing to the narrowing of the skill-based wage gap.

Table 6. OLS regression result of aggregate model

Source	SS	df	MS	Number of obs	19
				F(2, 16)	17.05
Model	563.934345	2	281.967173	Prob > F	0.0001
Residual	264.568139	16	16.5355087	R -squared	0.6807
				Adj R -squared	0.6408
Total	828.502485	18	46.0279158	Root MSE	4.0664

SkillLWageGap	Coefficient	Std. err .	t	P> l tl	[95%conf.	interval]
MinWageincreas	-.153334	.065377	-2.35	0.032	- .2919261	- .014741
LnSkilledEmpRatio	-.255340	.061841	-4.13	0.001	-.386436	-0.12424
-cons	.306722	.099383	3.09	0.007	.096039	0.517405

Source: Author's own calculations. Minimum wage increase series is provided from the Ministry of Labor and Social Security and is deflated by consumer price index. Skilled employee ratio is computed using HLFS microdata.

Table 7. Summary statistics for the OLS model

Variable	Observations	Mean	Std. Dev.	Min	Max
Skill Wage Gap (%)	20	66.0667	7.0842	52.7905	75.0321
Min Wage Inrease (%)	20	22.6714	24.5390	6.7605	104.1177
Ln of Ratio of Skilled Employees	20	3.1010	.1750	2.8118	3.3830

Source: Author's own calculations

5. Conclusion

This study examines the impact of minimum wage changes and the proportion of skilled labor in the workforce on the skill-based wage gap in Turkey. We utilize microdata from the Household Labor Force Survey (HLFS) provided by the Turkish Statistical Institute, covering the period from 2004 to 2023. By leveraging the large sample size of the HLFS, we first analyze wage disparities between skilled and unskilled groups through a Heckman-type wage equation that accounts for sample selection. Subsequently, we compute the skill-based wage gap for each year within the specified period using the Blinder-Oaxaca decomposition technique. In the final stage of the analysis, we apply an OLS method where the wage gap, derived from the microdata, serves as the dependent variable. The explanatory variables include the proportion of skilled labor in employment (calculated from the microdata) and real minimum wage changes, adjusted for inflation by deflating the average annual nominal increase. This methodology allows us to explore the issue from a broader macroeconomic perspective.

The results from the Heckman wage equations reveal significant differences in the influence of factors such as age, firm size, employment type, and employment status on wage determination and job-finding probabilities between skilled and unskilled workers. Notably, age has a stronger effect on both wage levels and job-finding prospects for skilled workers, while informal employment has a more pronounced negative impact on unskilled workers. Additionally, we find that the skill-based wage gap is narrower in the public sector compared to the private sector. An unexpected finding is that the negative effect of marriage on job finding is more pronounced for skilled workers. The OLS regression analysis, which investigates the aggregate factors affecting the skill-based wage gap, suggests that a 1% increase in the minimum wage results in a 0.15% reduction in the wage gap. Furthermore, a 1% increase in the share of skilled workers in the labor force leads to a 0.26% reduction in the wage gap. These findings indicate that the wage premium associated with education is steadily diminishing over time, which may result in a future decline in the demand for university education.

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