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Research paper

Why Is The Evolution of Urban-Rural Wage Disparities in Bangladesh Slow?

Md Aminur Rahman

Assistant Professor, G2 Big Data Management Department, Gangseo University
**Corresponding author E-mail: aminur.edu@gmail.com*

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Abstract

Instead of studying at a static point, this article has studied the dynamics of urban-rural wage disparities in Bangladesh by analyzing cross-sectional data derived from the labor force survey conducted during two distinct periods. The study utilizes the Juhn–Murphy–Pierce (JMP) decomposition method and extends it by adding propensity score matching (PSM) to derive empirical results. Moreover, the bootstrapping method determined the significance level of the empirical result. The findings of the study demonstrate that the pace of the reduction of the wage gap is impeded, mainly due to human capital and urban-centric industries. Based on the findings, it is recommended to prioritize investments in education and skills development and make policies to attract educated and skilled labor in rural areas. This paper provides informative details about the wage disparities between urban and rural areas in Bangladesh, which could be advantageous for academicians, researchers, planners, and policymakers.

Keywords: *Bangladesh, Dynamic decomposition, regional wage differentials, Labor economics, Urban-rural wage gap.*

1. Introduction

Over the past few decades, the economic landscape of developing countries, including Bangladesh, has undergone significant changes due to rapid urbanization. As urban areas continue to expand, the issue of wage disparities between urban and rural laborers has become increasingly concerning. Promoting fair and equitable economic development is necessary, as it is believed that extremely unequal nations have significant urban-rural disparities (Roback, 1988).

One key interesting feature of the urban-rural wage gap is its widening during the early stages of industrialization. However, as urbanization continues and advancements in science and technology continue, the gap gradually narrows (Borodkin et al., 2008). There are numerous reasons behind the existence of the urban-rural wage gap. Urban areas, characterized by the concentration of industries, businesses, and services, offer a multitude of employment opportunities, leading to heightened competition among employers and subsequently higher wages (Vera-Toscano et al., 2004). Differing factor intensities between urban and rural areas also produce differences in the ratio of skilled to unskilled workers between the two areas, leading to higher wages in urban areas compared to rural areas (Young, 2013). Additionally, the industry composition in urban areas tends to be more diverse, encompassing sectors like finance, technology, and professional services that offer higher wages. On the other hand, rural areas are often dominated by industries that offer lower pay, which collectively contribute to the significant wage gap between urban and rural areas (Dauth et al., 2016). According to the research of Dickie and Gerking (1998), worker immobility and market segmentation are two additional factors that contribute to rural-urban pay disparities.

The purpose of the study is to analyze the urban-rural wage disparities in Bangladesh. In the last decade (2010-2020), the urban population of Bangladesh grew from 36 million to nearly 42 million (BBS, 2020). Concerning this, the Bangladesh government has implemented various public policies. For example, the implementation of the Bangladesh Labor Rules (BLR) 2015 to ensure the productivity and well-being of the laborers responds appropriately to their concerns related to basic wages and reduces regional wage disparities. Acknowledging this, the purpose of the study is to analyze the urban-rural wage disparities in Bangladesh, and the author is motivated by a couple of research questions. The first question is whether the urban-rural wage gap is reducing over time. The second question is, what are the factors that prevent the gap from being eliminated?

To the author's knowledge, there are no studies that have specifically examined the urban-rural wage gap in Bangladesh. The literature on the wage gap in Bangladesh primarily focuses on the gender wage gap, with less emphasis on the wage gap in other areas. Rahman and Kim's (2023) attempt to determine the sectoral wage gap identified a notable exception. Since the study on the urban-rural wage gap in Bangladesh is scarce, the necessity of studying this is easily assumable, and the purpose of the study is to provide empirical evidence on the urban-rural wage gap in Bangladesh. More specifically, this study aims to investigate the changes in the urban-rural wage differential in Bangladesh between 2009 and 2016 and explore the potential factors that contribute to this wage gap. With a view to doing that, first, it investigates whether the urban-rural wage disparity has changed over the past decade. Second, it analyzes the impact of various factors that influence this wage gap.

This study contributes to the understanding of regional wage disparities by identifying the role of observed and unobserved components. The study uses cross-sectional data from Bangladesh's labor force survey from two different times, 2009–10 and 2016–17. To get empirical results, it uses the Juhn–Murphy–Pierce (JMP) decomposition method, which was developed by Juhn, Murphy, and Pierce (1991, 1993). The conventional Oaxaca (1973) and Blinder (1973) decomposition method breaks the wage differential into two components: differences in average characteristics and differences in the returns to these characteristics, while JMP decomposition yields details about the elements that account for variations in regional wage disparities over time. Since the JMP decomposition is based on ordinary least squares (OLS) estimates, our study expands on their method by incorporating the propensity score matching (PSM) to analyze the urban-rural wage differential specifically within the private sector of Bangladesh.

This paper is further structured as follows: Section 2 reviews the theoretical and empirical studies. Section 3 outlines the model specification and estimation technique. Section 4 consists of the estimation and interpretation of the results. Finally, Section 5 presents the conclusion.

2. Literature Review

Two fundamental theories of wage determination are proposed to explain regional wage differentials: the neoclassical theory and the institutional theory.

Neoclassical theory asserts that the supply and demand for labor in various regions determine wages. According to neoclassical economics, wages will equalize across regions over time as labor and capital move to where they can achieve the highest returns. This movement is driven by competitive forces, and differences in wages across regions are expected to be temporary, reflecting short-term imbalances in labor markets. The theory suggests that real wages will equalize as workers and firms adjust to changes in economic conditions, considering factors like cost of living and available amenities. This means neoclassical theory predicts wage equalization across regions, focusing on real wages rather than nominal wages (Sahling & Smith, 1983; Davis & Haltiwanger, 1991; Romer, 2018; Mankiw, 2021).

Many economists and industrial relations experts argue that understanding large and persistent regional wage differentials requires looking beyond the neoclassical model. In the past decade, increasing research has focused on the role of institutional factors in the wage adjustment process. Institutional theory emphasizes the role of institutional factors in determining wages, which include unions, discrimination (based on race or gender), market concentration, and other non-competitive forces. (Freeman, 1993; Autor, Dorn, & Hanson, 2013; Blau & Kahn, 2017). Institutional theory suggests that these factors can create persistent wage differentials by affecting labor market conditions and wage-setting processes in ways that go beyond simple supply and demand. Institutional factors can lead to wage rigidity and disparities that are not easily explained by neoclassical models. For example, the impact of labor unions and discriminatory practices can contribute to ongoing regional wage differences by influencing wage negotiations and employment conditions in various regions (Card & Krueger, 1995; Piketty, 2014; Blau & Kahn, 2017).

The extent to which urban-rural wage disparities are due to the skill composition of the workforce versus non-human endowments such as infrastructure, etc., is an essential question. According to Roca and Puga (2017), employees' wages are not initially higher in larger cities; rather, it is their work in cities with varying densities that causes their income to diverge over time. Using the AKM (Abowd et al., 1999) decomposition method, it was demonstrated that education, occupation, and industry-specific inequality were the results of workplace-specific characteristics and that they were not inherently urban phenomena. As an example, excellent companies hire the best employees and compensate them adequately, which is considered a reasonable management practice. The study concluded that, on an individual level in France, the firm effect is relatively less significant than the person effect. On the other hand, the framework of Young (2013) strongly argued that a huge and exceptional wage gap in a country, no matter whether it is poor or rich, is only due to the sorting of skills.

Because of widening regional disparities, research suggests that foreign direct investment (FDI) increases inequality (e.g., Zhang and Zhang, 2003). Contrary to popular belief, Wang et al. (2021) conducted a study on inward foreign direct investment (FDI) and its effects on urban-rural wage inequality in China and found that inward FDI does not exacerbate urban-rural wage inequality. Their study was based on a panel dataset containing thirty provinces and localities. By determining the association between FDI and geographical wage disparity using spatial econometric methodologies to account for total, direct, and indirect effects, the author filled a significant gap in the literature. It is widely believed that misallocation of resources explains differences in regional income and productivity within a country. Weak institutions and infrastructure in rural areas result in discrimination and lower levels of income generation. However, if labor forces are spatially mobile, local demand and supply have little influence on local wages (Rosenzweig and Mark, 1978).

Regional wage differentials have been decomposed by several prior researchers (i.e., Cotton, 1993; Eberts and Schweitzer, 1994; Oaxaca and Ransom, 1994; Carlstrom and Rollow, 1998; Garcia and Molina, 2002). These analyses are carried out from a static point of view, utilizing the decomposition method established by Oaxaca (1973) and Blinder (1973). The Oaxaca-Blinder decomposition has limitations since it considers the elements that contribute to wage differentials at a specific point in time. While Juhn, Murphy, and Pierce (1991, 1993) presented a method popularly known as JMP that tackled those problems and enabled dynamically decomposing wage differentials. The JMP allows a more diverse breakdown of wage differentials than the Oaxaca-Blinder approach by explaining variations.

A few recent and relevant studies are highlighted for further insight. Pereira and Galego (2007) explored spatial wage differentials in Portugal from 1995 to 2002, using dynamic methodologies, particularly the Juhn, Murphy, and Pierce (JMP) decomposition, to analyze wage changes over time. The study highlighted significant wage disparities between Lisboa and other regions, driven by differences in educational attainment and occupational structure. While regional endowments widened the wage gap, other factors helped to narrow it. The paper critiques previous static analyses for lacking dynamic insights and suggests policy interventions like reducing municipal taxes and improving labor mobility to address persistent wage inequalities across regions.

Lim and Cho (2009) studied interregional wage differentials in Korea, particularly between the capital and non-capital regions, focusing on the role of productivity-related characteristics and market valuation. It decomposes wage gaps into differences in worker characteristics, market returns, and unexplained factors. The findings reveal that 26.9% of the wage differential is due to differences in education and firm size, while 73.1% is attributed to residual factors, possibly discrimination. The study emphasizes the importance of occupation in explaining wage disparities and calls for further research into unobserved characteristics to better understand these wage gaps.

Ghosh and Lee (2016) examined the significant rise in wage inequality in South Korea between 1998 and 2007, a period shaped by the Asian financial crisis and preceding the global financial crisis. Using data from the Korean Labor and Income Panel Survey and two decomposition methods, the authors explore the impact of education and unionization on wage distributions. They find that changes in educational attainment account for around 10% of the increase in upper-wage inequality, while the decline in unionization plays a minimal role. Shifts in labor force composition significantly affect wage inequality, particularly among higher earners. The study calls for policy interventions such as improved access to education and labor market reforms to reduce wage disparities and promote a more equitable labor market.

Kim and Kim (2020) examined labor share trends in Korea, showing that while regional labor shares generally align with national trends, significant variations exist, especially in industrial regions sensitive to external shocks. A shift-share decomposition reveals that changes within regions largely drive aggregate labor share fluctuations, with shifts contributing positively from 2000-2006 and negatively from 2006-2014. The analysis highlights the importance of regional dynamics, such as aging firms and market concentration, which negatively affect labor share. The findings suggest that policymakers should develop region-specific strategies, particularly in labor-intensive provinces, to address labor share declines.

Ananian and Dellaferrera (2024) showed the urban-rural wage gap among 58 countries. Surprisingly, the observed variables explain only half of the wage gap. Thus, the authors emphasized government intervention in setting minimum wages. Although government intervention may improve the wage gap situation, its effects may also disrupt the market forces. That is why the government cannot be the sole solution to eradicate the urban-rural wage gap. Rather, benefitting rural markets from the agglomeration effect can be an addition to solve the problem, as suggested by Brixy et al. (2022).

The literature on urban-rural wage gap estimation in Bangladesh is scarce. However, there are numerous studies on rural-urban migration, which is the most important determinant and predictor of regional inequality in terms of economic prospects and living standards. According to the widely established Todaro hypothesis, wage gaps cause rural-urban migration (Todaro, 1969). Recently, a study found that a greater proportion of men (85.3%) migrated to urban areas for employment-related reasons such as seeking new employment, a higher income, or a change in services (Rahaman and Ahmed, 2016). Similarly, Ishtiaque and Mahmud (2017) found that a total of 52.3% of men migrated to the slum areas of the Dhaka city corporation, and out of those, 88.7% migrated for employment. In fact, Akter (2005) highlights that 70% of the total wage disparity in rural Bangladesh is due to workplace discrimination.

3. Model Specification

3.1 OLS, JMP, and wage difference over time

This study initially aims to investigate the dynamic changes in wage differentials between the rural and urban regions in Bangladesh by applying the Juhn–Murphy–Pierce (JMP) decomposition method. Table 1 displays the variables employed in the analysis and their descriptions.

Table 1: Variable description

Variable	Measurement
Age	Age of the individual (years)
Experience	Number of years of experience in the labor market (= age - education year - 6)
Married Dummy	1 = married, 0 = never married
Education Dummy	Classified as no education (E1), primary (E2), secondary (E3), post-secondary (E4) and graduates
Industry Dummy	Classified as agriculture (I1), manufacturing (I2), service (I3) and others (I4)
Occupation Dummy	Occupations included managers, professionals, clerical, service and sales, skilled agriculture, Craft and related trade, and plant and machine operator dummies

Source: Labor Force Survey (LFS), Bangladesh Bureau of Statistics. Retrieved from https://webapps.ilo.org

The reason for choosing this estimation method is that this method permits the decomposition of wage differentials into more diverse components and can explain changes in wage differentials over time. Few scholars have concentrated on the dynamic decomposition of the urban-rural wage gap, despite the abundance of regional and urban-rural wage gap estimations. To estimate this dynamic decomposition, the JMP method has proven to be efficient. For example, Pereira and Galego (2011) and Kim et al. (2015) used the JMP decomposition method to determine the change in wage gap over time.

First, the wage equation of the benchmark region (urban) is estimated.

$$Y_{it}^{u} = X_{it}^{u} * \beta_t^{u} + \varepsilon_{it}^{u} \tag{1}$$

Where Y_{it}^{u} is the natural log of an individual's hourly income in the urban region, at time t. $\boldsymbol{X_{it}^{u}}$ is the vector of observed attributes of urban worker i (or productivity-related endowment), at time t. β_t^{u} is the estimated coefficient, and ε_{it}^{u} is the associated residual vector. Using the urban area coefficient value from Equation 1, it is possible to determine the hypothetical wage equation for rural areas. It is assumed that rural wage earners were compensated according to the urban pay structure. Yet, the qualities associated with production were preserved. The following is the form that the hypothetical wage equation for rural areas takes:

$$Y_{it}^{r} = X_{it}^{r} * \beta_t^{u} + \varepsilon_{it}^{*r} \tag{2}$$

ε_{it}^{*r} is the residual that is obtained when the urban coefficient is used rather than the rural coefficient.

Using the standard deviation of urban area residuals (σ_t^{u}We may estimate the standardized residual for rural regions, which will be used in the subsequent phase of the decomposition.

$$\theta_{it}^{*r} = {\varepsilon_{it}^{*r}}\Big/{\sigma_t^{u}}.$$

$$\bar{\varepsilon}_{it}^{*r} = \sigma_t^{u} \,.\, \bar{\theta}_t^{*r}.$$

Using the mean difference in the average wage earned in rural and urban areas over a particular period, the average wage gap across regions can be broken down into its parts.

$$\begin{aligned}\bar{D}_t &= \bar{Y}_t^{u} - \bar{Y}_t^{r} \\ &= (\bar{X}_t^{u} - \bar{X}_t^{r})\beta_t^{u} + (\bar{\varepsilon}_t^{u} - \bar{\varepsilon}_t^{*r}). \\ &= (\bar{X}_t^{u} - \bar{X}_t^{r})\beta_t^{u} + \sigma_t^{u}(\bar{\theta}_t^{u} - \bar{\theta}_t^{*r}). \\ &= \Delta\bar{X}_t\beta_t^{u} + \sigma_t^{u}\Delta\,\bar{\theta}_t\end{aligned} \tag{3}$$

When decomposing the average pay differentials, two components were revealed. The first factor is the overserved characteristics multiplied by the returns to urban workers (β_t^u). The next unobserved component is the change in standard residuals multiplied by the price measure on these attributes (σ_t^u).
Lastly, equation 4 can be used to measure the difference in regional wages between two time periods. Let's assume that t = 1 in 2016-17 and t = 0 in 2009-10. Hence, the regional wage gap between 2016–17 and 2009–10 is calculated as follows.

$$\bar{D}_1 - \bar{D}_0 = (\Delta\bar{X}_1\beta_1^u - \Delta\bar{X}_0\beta_0^u) + (\sigma_1^u\Delta\,\bar{\theta}_1 - \sigma_0^u\Delta\,\bar{\theta}_0).$$
$$= (\Delta\bar{X}_1 - \Delta\bar{X}_0)\beta_1^u + \Delta\bar{X}_0(\beta_1^u - \beta_0^u) + (\Delta\,\bar{\theta}_1 - \Delta\,\bar{\theta}_0)\sigma_1^u + (\sigma_1^u - \sigma_0^u)\Delta\,\bar{\theta}_0 \quad (4)$$

Observed productivity-related features over time constitute the first term on the right-hand side of Equation (4). The second term is the observed price effect, which reflects the consequences of changes in the observed characteristics' prices. The gap effect analyzes the disparities in salaries or unobserved skills between two groups over time. The fourth and final term is the unobserved pricing effect, which is defined as the change in returns to unobserved productivity or skill.

3.2 PSM, JMP, and wage difference over time

In observational research, propensity score matching balances treatment and control groups. Propensity score matching (PSM) can match urban and rural workers with similar observable characteristics for urban-rural wage comparison. This method selects two urban and rural subsamples with similar characteristics to create a common support counterfactual wage. Rosenbaum and Rubin (1985) devised the PSM methodology to eliminate the selection bias produced by the B–O method and its variants by matching samples with similar observable characteristics. The PSM method is particularly relevant to this article because sample selection bias is less of a concern in this study, which does not compare female and male wage equations (Pereira and Galego, 2007).
Let us assume that Y_1 represents the earnings if the individual received treatment (urban resident in our study), and that Y_0 represents the earnings if the individual did not receive treatment (rural resident). Let us denote the binary indicator of the actual treatment received as D $\in \{0,1\}$, while X is a set of attributes that are unaffected by the treatment (demographic, occupational, and workplace-related).
We are interested in evaluating the impact of treatment on individual i in comparison to untreated individuals ($Y_1 - Y_0$). The PSM must maintain the conditional independence assumption (CIA). The CIA can be represented by the equation as shown below:

$$(Y_1, Y_0) \perp \mathrm{D}|\mathrm{X}, \qquad 0 < \mathrm{pr}(\mathrm{D} = 1|\mathrm{X}) < 1$$

Where $\perp$ denotes independence. This study generates groups of similar urban and rural individuals based on the probit model's propensity score estimation. As one of the matching measurements, the current study has used nearest-neighbor matching on a 1:1 basis.

3.3 Data Description:

This study uses cross-sectional data based on the labor force survey of the Bangladesh Bureau of Statistics (BBS) over two different periods, 2009-10 and 2016–17[1]. The research employs these two datasets to monitor the urban-rural wage gap throughout the era, which was characterized by a tranquil political climate and the absence of an epidemic such as COVID-19. Bangladesh experienced political instability in 2018 because of the quota reform movement, and the coronavirus epidemic caused economic difficulties in 2019, 2020, and subsequent years. Moreover, the recent dataset's availability in BBS was deemed inappropriate for analysis due to several missing variables. Consequently, the researcher selected the two datasets to do the investigation.
Table 2 presents summary statistics for all the variables over the two time periods: 2009-10 and 2016-17. Additionally, the data is divided into genders: male and female. The comparison of the categories reveals several significant values. The urban females earned approximately 3.854 in log hourly salary in 2016–17, which is slightly higher than their rural counterparts, who earned approximately 3.785. In the same vein, urban males earned a marginally higher wage of approximately 3,960 than their rural counterparts. In urban areas, the average wages for both males and females were somewhat greater during the 2009–10 period, too.

Table 2: Summary of the variables

	2016-17				2009-10			
	Urban		Rural		Urban		Rural	
	Female	Male	Female	Male	Female	Male	Female	Male
Log hourly wage	3.854	3.960	3.785	3.858	3.110	3.237	3.076	3.080
Age	32.192	34.569	34.671	35.216	29.959	34.610	35.620	35.250
Experience	20.852	21.511	23.780	23.589	20.434	23.884	27.170	26.345
Married (%)	83.76	76.29	89.15	75.78	74.66	76.29	85.60	75.85
No education	31.728	18.232	38.524	33.568	43.121	32.441	60.344	50.317
Primary	26.443	26.411	22.597	30.268	28.077	26.199	18.323	25.397
Secondary	26.479	33.419	29.192	25.656	20.917	29.416	18.001	20.679
Post-secondary	10.464	14.602	8.488	8.442	3.138	4.778	2.042	2.045

[1] The LFS 2016–17 survey gathered information from 493,886 individuals, whereas the LFS 2009–10 survey gathered information from 199,274 individuals. Both phases selected households and individuals using a multistage stratified random sampling design. This study focused exclusively on individuals employed in the private sector on a wage basis, using data from paid workers aged 15 years and older. We excluded public sector employees because their salaries are determined by governmental entities, eliminating potential wage disparities between urban and rural regions.

Graduate	4.655	7.207	1.068	1.930	4.747	7.166	1.290	1.561
Agriculture	2.731	6.178	22.672	34.501	5.390	13.504	32.348	52.622
Manufacturing	44.081	30.186	29.923	22.708	57.683	24.677	23.966	11.182
Service	50.262	47.133	41.859	26.034	32.502	48.180	34.713	24.852
Others	2.802	16.461	5.509	16.735	4.425	13.639	8.974	11.345
Elementary	30.655	16.438	39.329	42.413	27.514	37.411	54.057	68.010
Manager	1.357	6.350	0.693	1.973	0.724	1.811	0.322	0.423
Professional	13.541	9.751	11.486	6.240	5.471	3.313	5.212	2.393
Associate	2.040	4.304	1.986	2.168	2.735	2.601	2.203	1.398
Clerical	2.403	3.493	1.724	2.121	1.529	2.832	1.666	1.398
Service	6.633	16.927	8.900	9.099	5.792	15.334	12.574	6.675
Agriculture	0.390	0.861	2.473	3.916	0.644	1.984	0.967	2.052
Trade	36.854	31.671	26.176	24.418	13.516	16.567	12.574	9.620
Manufacturg	5.516	10.023	5.809	7.560	42.076	18.147	10.425	8.032
N	11,277	26,088	5,337	23,573	1,243	5,191	1,861	14,667

Source: Author's computation based on the LFS 2016-17 and 2009-10

When examining age, there was a notable difference between urban and rural populations. For both genders, the average working age of rural populations is slightly higher compared with their urban counterparts. Similarly, during the investigation period, individuals in rural areas had more work experience than those in urban areas.

The comparison of educational levels between 2016–17 and 2009–10 reveals some intriguing trends. In 2016–17, urban females had a lower average of individuals with no education (31.73%) compared to 2009–10 (43.12%). There was also a decrease in the percentage of urban females with primary education, from 28.08% in 2009–10 to 26.44% in 2016–17. The average score for females at the higher education level also changed. However, there has been a noticeable shift in graduate education, with the percentage of female graduates in urban areas dropping to 4.655 in 2016–17 from 4.747 in 2009–10.

Over the years, the educational status of males has shown some notable trends. For urban males, there was a noticeable decrease in the percentage of individuals with no education from 32.44% in 2009–10 to 18.23% in 2016–17. The average number of rural males without education also decreased, from 50.31% in 2009-10 to 33.57% in 2016-17. There was a slight increase in the proportion of rural males completing primary education, from 25.39% in 2009–10 to 30.27% in 2016–17. However, there was an increase in the percentage of rural males with secondary education, rising from 20.67% in 2009–10 to 25.65% in 2016–17. Overall, all groups had relatively low graduation rates, with urban males having the highest percentage (7.207%).

The analysis of industry and occupation shows that the manufacturing and service industries employed most people in 2016–2017. In contrast, the agricultural sector offered relatively more job opportunities in 2009–2010. In terms of profession, elementary and trade-related jobs accounted for more than half of the total job opportunities for both urban and rural females in 2016–17. Although the elementary job was found to be an influential sector of employment for males in 2009–10, the influence was deemed to have occurred in the later period.

4. Results and Discussions

4.1 Total wage gap

Prior to examining the results of the decomposition, it is crucial to ascertain if the propensity scores have achieved perfect matching or not. Assessing the balance of variables between the treatment and control groups is crucial in order to ascertain the effectiveness of the matching process. Ensuring a balance between treatment and control groups in propensity score matching (PSM) is crucial for enhancing the comparability of the groups, minimizing bias, and improving the validity and reliability of causal conclusions derived from observational studies. Additionally, the external validity of the study is enhanced by the appropriate balancing of the groups.

Table 3: t-Test after matching

	2009-10				2016-17			
	Mean			t-test	Mean			t-test
Variable	Treated	Control	Different	p>t	Treated	Control	Different	p>t
age	33.715	33.599	0.116	0.602	33.845	33.597	0.248	0.005
agesq	1295.200	1287.400	7.800	0.654	1292.800	1269.900	22.900	0.001
exp	23.221	23.169	0.052	0.830	21.307	21.143	0.164	0.110
female	0.193	0.184	0.009	0.207	653.540	643.570	9.970	0.081
expsq	726.050	726.840	-0.790	0.956	0.300	0.307	-0.006	0.054
married	0.760	0.764	-0.004	0.605	0.785	0.790	-0.005	0.098
prim	0.266	0.263	0.003	0.719	0.264	0.269	-0.005	0.150
second	0.278	0.265	0.013	0.100	0.313	0.311	0.002	0.532
psecon	0.045	0.044	0.001	0.830	0.134	0.130	0.003	0.159
grad	0.067	0.072	-0.005	0.226	0.064	0.062	0.002	0.223
manu	0.311	0.308	0.002	0.775	0.344	0.344	0.000	0.951
serv	0.451	0.451	0.001	0.929	0.480	0.481	0.000	0.895
other_ind	0.119	0.122	-0.004	0.533	0.124	0.123	0.000	0.938
managers	0.016	0.012	0.004	0.087	0.049	0.045	0.004	0.611
professionals	0.037	0.037	0.001	0.852	0.108	0.112	-0.004	0.782

associate	0.026	0.030	-0.004	0.167	0.036	0.031	0.005	0.000
clerical	0.026	0.021	0.005	0.062	0.032	0.026	0.006	0.000
service	0.135	0.118	0.016	0.005	0.138	0.137	0.001	0.617
agriculture	0.017	0.020	-0.002	0.325	0.007	0.007	0.000	0.731
trade	0.160	0.169	-0.009	0.154	0.333	0.347	-0.014	0.000
manufacturing	0.228	0.230	-0.002	0.737	0.087	0.084	0.003	0.128

Table 3 displays the balancing for the ATT (average treatment effect on the treated), where the treated serve as the reference group. The t-test was performed following the application of 1:1 nearest neighborhood matching. The results of the t-test imply that, in the majority of situations, there is no statistically significant difference between the means of the variables in the two groups. This finding implies that the matching process was successful in attaining balance.

Graphs were utilized in the study to visually depict the propensity score of both the control group (representing the rural area) and the treatment group (representing the urban area) after the application of matching techniques. The initial graph illustrates the data set for the year 2009–10, while the subsequent graph presents the data set for the year 2016–17.

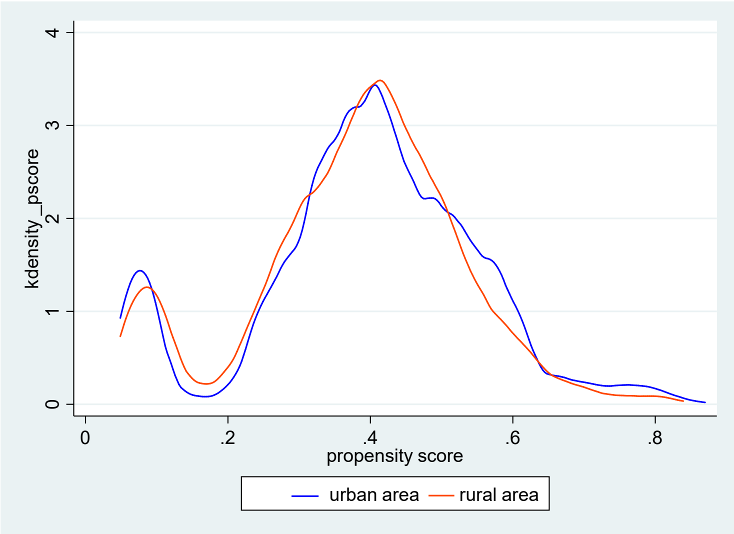

Fig. 1: PS score after matching (2009-10)

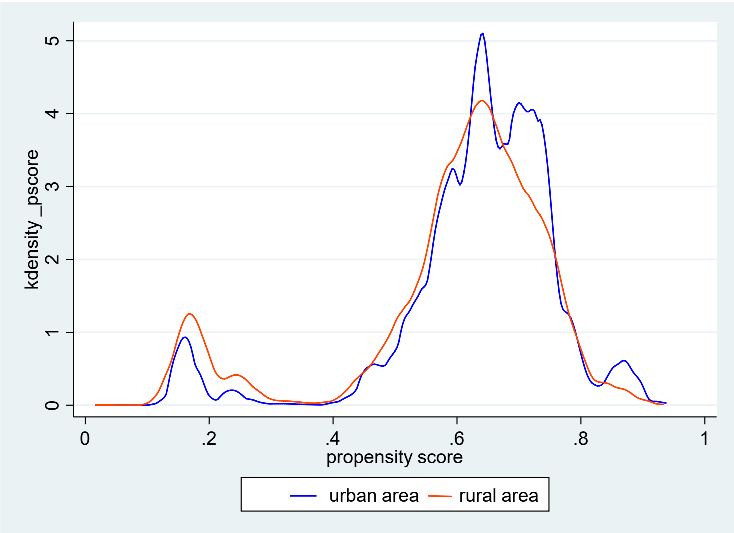

Fig. 2: PS score after matching (2016-17)

The estimated result of the urban-rural wage gap for the entire sample is presented in Table 4. The table includes the output of the general JMP decomposition and the JMP decomposition after PSM.

Table 4: Overall wage gap

	JMP	JMP using PSM
Observed X's effect (A)	0.040**	0.042*
	(0.018)	(0.024)
Observed price effect (B)	-0.069***	-0.013***
	(0.002)	(0.005)
Changes in observed components (C=A+B)	-0.029	0.029
	(0.018)	(0.024)

Gap effect (D)	-0.016* (0.009)	-0.056*** (0.005)
Unobserved price effect (E)	-0.010 (0.008)	0.008*** (0.003)
Changes in unobserved components (F=D+E)	-0.026 (0.027)	-0.048*** (0.000)
Total (C+F)	-0.055* (0.032)	-0.019 (0.024)

*Note: Standard error is in parentheses * is significant at 10 percent, ** is significant at 5 percent, and *** is significant at 1 percent.*

The results obtained from employing both methodologies demonstrated a decrease in the gap between wages in urban and rural areas. However, the estimation using the general JMP decomposition indicated a more substantial drop, amounting to 5.5 percent. Upon examining the impact of observed and unobserved components, the first estimating approach revealed that both components contribute consistently, specifically towards the lowering of the wage gap. The second estimation approach revealed that both observed and unobserved components have a countervailing impact on regional wage differentials. Specifically, the observed components were found to raise the wage gap by 2.94 percent, while the unobserved components contributed to narrowing the difference by 4.83 percent. The reduction in the total wage gap can be attributed to the prevailing influence of the unobserved components.

Upon doing the significance analysis using bootstrapping, it was determined that the observed effect of variable X has statistical significance for both estimation methods. Nevertheless, the conventional decomposition outcome using the JMP method yielded statistically significant results at a significance level of 5%. In contrast, the JMP method combined with propensity score matching (PSM) produced statistically significant results at a lower significance level of 10%. The statistical analysis revealed that the observed pricing impact exhibited a level of significance at the 1%. Moreover, it was discovered to have a negative sign in both estimation methods. This suggests that the observed price effect plays a role in diminishing the wage gap over time, irrespective of the specific estimate method employed. In relation to the phenomenon known as the gap effect, the subsequent estimate technique yielded findings indicating that the gap effect exhibits a negative value and possesses statistical significance at a confidence level of 1%. The utilization of bootstrapping proved to be the most significant consequence in detecting an unobserved pricing effect. The initial estimation approach had a negative outcome, whereas the subsequent approach offered a contrasting one. Through the application of bootstrapping, it was ascertained that the outcome of the second technique exhibits statistical significance. This finding consequently supports the inference that the unobserved price impact plays a contributory role in the gradual increase of the rural wage gap, amounting to a 0.08% increase over a given period.

In assessing the comprehensive urban-rural wage disparity, it can be observed that the wage gap has diminished from 2009-10 to 2016-17. However, it is worth noting that the extent of this reduction varied slightly across different estimating methodologies. The increase in the regional wage difference may be attributed only to the observed impacts of variable X.

4.2 Gender wage gap

The author has employed the same formula as previously mentioned to independently assess the disparity in regional wages between males and females. This was conducted to ascertain whether the salary disparity between genders exhibits a similar trend over time as observed in the whole sample, or if any divergences are evident. The author realizes the necessity of analyzing the wage gap among genders, as it can increase the reliability of the findings. Moreover, this kind of heterogeneity analysis can ensure that the total result does not hide the subgroup pattern. The T-test results after matching for both years and genders are presented in Table 5.

Table 5: t-Test after matching (gender)

	Female				Male			
	2016-17		2009-10		2016-17		2009-10	
Variable	Different	p>t	Different	p>t	Different	p>t	Different	p>t
age	0.162	0.283	-0.297	0.545	0.557	0.788	0.026	0.917
agesq	15.200	0.177	-28.100	0.448	47.600	0.326	1.000	0.959
exp	0.105	0.566	-0.769	0.160	0.536	0.912	-0.099	0.711
expsq	1.760	0.859	-44.260	0.162	26.120	0.785	-5.350	0.736
married	-0.004	0.392	-0.005	0.781	0.007	0.049	-0.003	0.764
prim	0.003	0.617	0.013	0.472	0.001	0.781	-0.003	0.738
second	0.003	0.563	0.015	0.342	-0.003	0.510	0.005	0.560
psecon	0.003	0.455	0.021	0.000	0.005	0.099	0.012	0.003
grad	0.000	0.975	0.003	0.701	-0.001	0.566	-0.005	0.330
manu	-0.012	0.062	0.002	0.903	0.003	0.417	0.001	0.909
serv	0.015	0.023	0.004	0.830	-0.003	0.435	-0.002	0.829
other_ind	-0.003	0.179	-0.013	0.144	0.000	0.944	-0.003	0.649
managers	0.007	0.000	-0.007	0.082	0.001	0.516	0.001	0.766
professionals	-0.005	0.285	0.010	0.226	0.002	0.495	0.001	0.869
associate	0.004	0.043	-0.001	0.903	0.006	0.001	0.002	0.573
clerical	0.002	0.326	0.006	0.206	0.004	0.021	0.002	0.507
service	0.004	0.220	0.007	0.426	-0.008	0.011	0.016	0.021
agriculture	-0.002	0.034	0.006	0.019	0.000	0.707	0.003	0.241
trade	-0.012	0.071	0.013	0.338	-0.007	0.076	-0.007	0.320
manufacturing	0.003	0.408	-0.004	0.839	0.001	0.589	-0.003	0.666

Table 6 provides assessments of the effects of observed and unobserved factors on wage differentials between men and women over time. Four columns of the table compare the propensity score matching (PSM) and ordinary least squares (OLS) techniques for analyzing the differences between the male and female categories. For both sexes, the estimated total effect of all observed and unobserved factors on the outcome is negative. The estimated value varies between -0.137 and -0.040, depending on the group and estimation method employed. This indicates that, on average, wage disparities between regions decreased between 2009-2010 and 2016-2017. However, it should be noted that the extent of these impacts varies depending on the group and estimation technique, suggesting that significant disparities could exist among different wage component segments.

The variations in the observed components are shown in the first row of Table 6. The estimated effect for females is 0.016 using OLS and 0.002 using PSM, while the estimated effect for males is 0.058 using OLS and 0.057 using PSM. After bootstrapping, each of the observed components was found to be statistically significant. The values of the observed X's effect show that characteristics have a greater influence on the wage difference for women. Based on the observed features, the wage difference for females tends to increase to a greater extent than for males. The estimated effect of price changes is then found to be positive for females, with estimates of 0.066 using OLS and 0.021 using PSM, and negative for males, with estimates of -0.096 using OLS and -0.019 using PSM. This is an intriguing result because males and females have opposing effects on the observed price effect, even though the results were statistically significant regardless of the categories and estimation method. This could be interpreted to mean that both the observed x's effect and its price contribute to increasing the regional wage disparity for females over time, while only the x's are responsible for increasing the gap in the case of males. Overall, the changes in the observed components (C=A+B) are positive for females regardless of the estimation method used, whereas OLS estimation indicates that the observed components of the wage disparity have decreased (-0.038 percent) for the time being for males, but PSM indicates the opposite. Therefore, the table indicates that the observed variations in components vary by gender. For females, the combined effect of observed X reliably increases the regional wage gap over time, whereas for males, the combined effect produces opposing results for various methodologies. Due to the magnitude of their elements, reversed output has occurred within the same group; therefore, the mixed-up result does not appear to be a cause of confusion.

Finally, looking at the changes in unobserved components, we found that the changes are negative in all four columns, suggesting that the inclusion of unobserved components reduces the regional wage gap for both females and males. The magnitude of the changes is greater for females than for males in both methods. This suggests that unobserved factors have a stronger negative impact on the outcomes of interest for females than for males. For females, the gap effect is estimated to be reduced by 11.7 percent using OLS and 13.8 percent using PSM, which means that even after the propensity score matching, the unobserved component trend reduces the urban-rural wage gap over time. For males, the pattern of unobserved components was found to be the same as that of females, except for the magnitude. Unobserved price also contributes to reducing the wage gap for both males and females, and both methods have confirmed this. Akin to the gap effect, the unobserved price also has a stronger negative effect for females. The significance level also provides evidence of their contribution to minimizing the regional wage gap, since all the effects were found to be significant.

The outcomes vary slightly depending on the method employed. However, the overall outcomes exhibit a high degree of consistency with the total outcomes. Hence, it can be asserted that there has been a decrease in the regional disparity in wages during the period under examination. Upon stratifying the sample by gender, we observed a consistent pattern in the overall results. Nevertheless, the most intriguing result refers to the impact of the observed price effect. It was determined to have contributed to the widening of the wage disparity for men, but to have been accountable for narrowing the gap for women.

Table 6: Changes in regional wage differentials

	Female		Male	
	OLS	PSM	OLS	PSM
Observed X's effect (A)	0.016*	0.002**	0.058***	0.057***
	(0.009)	(0.001)	(0.021)	(0.019)
Observed price effect (B)	0.066***	0.021*	-0.096**	-0.019**
	(0.021)	(0.090)	(0.041)	(0.009)
Changes in observed components (C=A+B)	0.082***	0.023	-0.038	0.038*
	(0.022)	(0.090)	(0.046)	(0.021)
Gap effect (D)	-0.117*	-0.138***	-0.060***	-0.076***
	(0.068)	(0.023)	(0.010)	(0.018)
Unobserved price effect (E)	-0.040***	-0.022***	-0.005**	-0.002**
	(0.013)	(0.011)	(0.002)	(0.001)
Changes in unobserved components (F=D+E)	-0.157**	-0.160***	-0.065***	-0.078***
	(0.069)	(0.025)	(0.010)	(0.018)
Total (G= C+F)	-0.075	-0.137***	-0.103**	-0.040
	(0.069)	(0.033)	(0.047)	(0.027)

*Note: Standard error is in the parentheses. * Is significant at 10 percent, ** is significant at 5 percent, and *** is significant at 1 percent.*

Since it was determined that the observed effect of x is responsible for the widening regional wage disparity, and the observed price effect has a countervailing effect on a different group, the authors believe this should be clarified. The Juhn-Murphy-Pierce (JMP) model places a strong emphasis on the significance of observed components in analyzing and comprehending changes in wage inequalities. The model analyzes the factors that contribute to variation in wages by specifically considering quantifiable characteristics such as education, experience, and occupation. This methodology allows researchers to identify patterns over a period, guide policy choices by identifying certain factors that contribute to inequality, and improve the clarity and openness of their findings. The focus on observed elements enhances the interpretability and accessibility of the study, offering useful insights into the changing dynamics of wage inequalities.

Table 7: Observed x's and price effect

	Observed X's effect (A)				Observed price effect (B)			
	Female		Male		Female		Male	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
age+agesq	0.045***	0.051***	0.001**	-0.001**	0.381**	0.280**	0.018*	0.000**
	(0.016)	(0.014)	(0.000)	(0.000)	(0.172)	(0.120)	(0.010)	(0.000)
exp+expsq	-0.043**	-0.054***	-0.000**	0.005	-0.454**	-0.296***	-0.084***	0.012
	(0.019)	(0.016)	(0.000)	(0.004)	(0.190)	(0.950)	(0.019)	(0.003)
education	0.003***	0.006***	0.007**	0.017**	0.065**	0.017*	-0.020**	-0.012***
	(0.001)	(0.002)	(0.004)	(0.008)	(0.030)	(0.009)	(0.008)	(0.003)
industry	0.024***	0.008***	0.012*	0.004**	-0.039***	-0.040***	-0.051***	-0.001**
	(0.010)	(0.003)	(0.007)	(0.002)	(0.013)	(0.011)	(0.019)	(0.000)
occupation	-0.017*	-0.017**	0.039**	0.041***	0.120***	0.064**	0.001**	-0.017**
	(0.009)	(0.008)	(0.017)	(0.015)	(0.036)	(0.027)	(0.000)	(0.008)

Note: Standard error is in the parentheses. * Is significant at 10 percent, ** is significant at 5 percent, and *** is significant at 1 percent.

To facilitate comprehension of the observed effects of X and price, Table 7 presents the contribution by category. Oaxaca and Ransom (1994) state that the dummy variables represent deviations from the grand mean instead of the reference category, which is why we chose not to include them in Table 7. Observed X's effect in the case of females revealed that age contributed to the widening of the wage disparity, while experience contributed to its narrowing in both estimation types. OLS estimates revealed a 4 percent increase in wage disparity due to age and a 4 percent decrease due to experience. The PSM estimation, on the other hand, revealed the same pattern for age and experience with a magnitude of approximately 5 percent. Education and industry contribute to the widening wage disparity, while occupation helps to narrow it. The observed effect of X on males varies depending on the estimation method. However, education and industry types appeared to be significant contributors to wage inequality according to both approaches.

Examining the observed price effect, we discovered that age increases the wage disparity in both categories and methods. In the case of women, experience contributes to a reduction in the wage disparity of approximately 4.5 percent by OLS estimation and 2.9 percent by PSM estimation. unfortunately, the results of experience were inconsistent among males. While OLS estimation indicated a reduction of approximately 8.4%, PSM estimation indicates an increase of 1.24 % in the wage gap. the contribution of education to the wage disparity for women was found to be positive, while the contribution for men was negative. The results of the industry's contribution to the observed price effect are highly consistent and indicate that it contributes to the reduction of the wage disparity regardless of the group or estimation method. Except for males by PSM estimates (-0.017 percent), occupation was found to exacerbate the wage gap.

5. Conclusion

The regional wage gap narrows, usually in two different circumstances. The first case is the increase in productivity-related characteristics of a reign with low wages, or conversely, their decline in a reign with high wages. The second scenario is when the relative influence of wage determinants increases in a low-wage region or decreases in a high-wage region. In the case of Bangladesh, we found a reduction in the urban-rural wage gap.

Given the limitations inherent in traditional methods of wage gap estimation, we have leveraged the capabilities of JMP decomposition to enable a more comprehensive examination. This methodology permits the decomposition of wage disparity into discrete elements, including observed and unobserved factors, as well as quantity and pricing considerations. Moreover, the inclusion of PSM to JMP is an addition to the urban-rural wage gap estimation in Bangladesh. The technique of bootstrapping was employed to ultimately obtain an estimation of the level of significance. The estimating method facilitates policy recommendations by determining which wage components contribute to the gap widening or narrowing.

The primary limitation of the JMP method is its reliance on residuals, as it is unable to discern the specific economic variables responsible for the fluctuations in unobserved components. Hence, providing commentary on the unobserved components posed a significant challenge. Since unobserved components are not directly observable in the data, a qualitative analysis can better explain this part. Based on an analysis of this article, it appears that the aggregate wage disparity in Bangladesh experienced a decline from 2009–10 to 2016–17. Moreover, when gender was considered, the outcomes showed a similar pattern; the only exception was found in the case of the changes in observed components of females. A notable outcome of the analysis is that observed factors are mainly responsible for the slowing of the evolution of the urban-rural wage gap. Because of that, explaining the unexplained components did not become the focus of this article. After a detailed examination of the observed variables and the price effect, the study found that experience played a significant role in reducing the wage gap. Education and industry were found to be responsible for the growing wage gap in both genders. The outcome was quite like the study of Kim et al. (2015), which indicates that the changes in observed components contribute more to widening the regional wage gap in Korea.

Policies may be formulated based on the findings. The study indicates that age, education, and industry are the primary variables contributing to the widening urban-rural wage difference. To address the widening wage gap between urban and rural regions, it is essential to implement comprehensive and particularly designed policies. Considering the educational and industrial contributions is essential, since previous studies (i.e., Ghosh and Lee, 2016; Pereira and Galego, 2007) have also emphasized these two elements.

The prioritization of enhancing educational opportunities in rural regions is crucial since there is evidence of regional heterogeneity in wage distribution in returns to education in the case of emerging countries (i.e., Herrera-Idárraga et al., 2016). The impact of education on spending inequality in three ASEAN countries (Indonesia, Myanmar, and the Philippines) also demonstrated that reducing the disparity in education between urban and rural areas could contribute to the reduction of overall spending inequality by reducing the disparity in spending between urban and rural areas (Akita & Miyata, 2021). Therefore, our initial policy recommendation is to guarantee that all individuals have the same opportunity to pursue their education in both urban and rural areas.

The simultaneous enhancement of job prospects and incomes can be achieved by implementing skills development programs, industrial incentives, and agricultural modernization initiatives to foster various industries in rural regions because a school of thought believes that the regional wage gap appears due to skill and efficiency (i.e., Young, 2013; Autor et al., 2006; Goos et al., 2009). To promote labor mobility and attract people with higher education and greater skills to rural regions, the improvement of transportation networks and technological infrastructure is essential. Urban areas offer a diverse array of employment opportunities due to their concentrated number of industries, enterprises, and services, which in turn results in increased competition among employers and, consequently, higher wages (Vera-Toscano et al., 2004). Due to inadequate infrastructure, rural regions in Bangladesh are incapable of creating such competition. Additionally, it is not inherently an urban phenomenon; rather, it is a prudent management strategy (Abowd et al., 1999). Infrastructure development might encourage the establishment of small enterprises and promote entrepreneurship. The economic sectors with significant potential for value creation may substantially enhance economic development in these regions. Additionally, the establishment of regional development initiatives and the implementation of modern agricultural practices have the potential to mitigate wage disparities.

In Bangladesh, the urban-rural wage disparity has decreased over time, which is a positive development. To achieve a more equitable labor market, additional steps are required. Our analysis emphasizes the need for investments in education and skills development to reduce disparities. Specifically, skill development initiatives such as digital and ICT, technical and vocational training, and soft skill development are suggested to improve productivity and marketability for the rural population. Improvements to rural infrastructure are also crucial for attracting investments and enhancing living conditions, which can contribute to an increase in rural wage opportunities. In order to adequately respond to dynamic economic issues and inequality, these policies must undergo regular assessment and adjustment. These recommended policies can enable policymakers to develop strategies that will eradicate regional wage discrimination in Bangladesh.

The study will help the researchers to understand the dynamics of the regional wage gap in Bangladesh. This study may offer new perspectives in this field, as no previous study has explained the urban-rural wage gap in Bangladesh. Future research could focus on determining the wage gap and examining the dynamics between metropolitan and non-metropolitan areas, or it could identify the gap between any two regions. In both cases, researchers may utilize the method applied in this article and consider this article as a foundation for urban-rural wage gap estimation in Bangladesh.

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