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Gender Wage Disparity in Urban India: An Analysis Using Unconditional Quantile Regression

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Abstract

A "wage gap" refers to disparities in pay among different employee groups. This study explores the gender-related wage gap within India's urban labor market. It employs Unconditional Quantile Regression (UQR) and Oaxaca-Blinder Recentered Influence Function (OB-RIF) Decomposition to analyze data from the Periodic Labour Force Survey for the year 2022-23. Our research thoroughly examines the impact of various covariates on unconditional wage quantiles, uncovering complex factors that contribute to gender-based wage differences. The UQR method revealed significant negative correlations between age and wages, the negative impact of caste on male wages, and the influence of marital status and education across different wage quantiles. Employment, enterprise, occupational, and industrial categories are critical wage penalties and premium determinants. The OB-RIF Decomposition highlights a significant and persistent gender wage gap, primarily attributed to discrimination rather than observable characteristics. However, a narrowing and eventual reversal of the gap at higher wage levels showed that characteristics favored females or were more advantageous to females in higher wage distributions. The study's innovative methods offer a comprehensive framework for analyzing wage inequality and gender disparities, providing essential guidance for future research and policy to foster a more equitable labor market.

Keywords

Decomposition, India, RIF, UQR, Wage Inequality

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Introduction

The wage gap represents a significant phenomenon within labor economics, underscoring disparities in pay across different workforce segments, with a particular emphasis on gender-based compensation differences. This issue garners widespread academic attention due to the stark gender-related income disparities evident when comparing male and female earnings. Such disparities are especially pronounced in the Indian subcontinent, where the gender wage gap significantly differs throughout urban areas, indicating the influence of a complex array of factors beyond mere variations between genders. Despite India's economic growth and progressive legislation, the gender disparity in earnings persists, particularly in urban sectors. Historically, the wage disparity showed a slow but steady decline. In the early 1990s, urban Indian females earned approximately 48 percent compared to men in similar positions. By 2018-19, this gap had narrowed to 28 percent, yet it still underscores a substantial inequality in earnings (Walter & Ferguson, 2022). Data from the Periodic Labour Force Survey (PLFS) for 2021-22 have highlighted that regular urban female employees earned about Rs. 4,800 monthly compared to Rs. 6,300 for males, marking a 24 percent wage gap. Additionally, urban casual laborers saw females earning Rs. 333 daily versus Rs. 483 for males during the same period, representing a 31 percent disparity (Ministry of Labour and Employment, 2023). The academic study of the gender pay disparity in India remains a focal point of interest. Deshpande et al. (2018) showed that in India's regular/salaried positions, women earn less than men. Additionally, their research emphasized the existence of a "sticky floor" phenomenon in India, where the gender pay gaps are more significant at the lower levels of the wage scale. Similarly, Sengupta and Puri (2021) emphasized that the wage disparity is not only about unequal pay but also reflects more profound inequalities in the labor market, such as unequal access to education, job segregation, and the underrepresentation of females in decision-making positions. The gender wage gap in urban India is a complex problem that reflects deep-rooted inequalities in the labor market. It points to the necessity for comprehensive strategies to tackle the root causes of this persistent problem.

Most research predominantly employed aggregate wage data to investigate mean wage disparities, leaving a significant gap in applying advanced statistical methods such as Unconditional Quantile Regression (UQR) within the Indian context. Introduced by Firpo, Fortin, and Lemieux (2009, 2018), UQR offers a substantial methodological advancement for analyzing the gender wage gap. This technique allows for a detailed examination across various wage strata, surpassing the limitations of Ordinary Least Squares (OLS) regression, which primarily assesses the impact of covariates on average outcomes. UQR's ability to evaluate covariate effects at multiple distribution points provides a more nuanced and intricate perspective on gender-based wage differences, thereby avoiding the oversimplifications associated with average-focused assessments. This method acknowledges the significant variation in how variables interact at different distribution points, as Waldmann (2018) and Sengupta & Puri (2021) highlighted. Furthermore, the integration of a UQR decomposition approach, formulated by Firpo et al. (2009), is employed to separate the gender wage gap across the entire wage distribution. Traditional Oaxaca-Blinder

(OB) decomposition, pioneered by Blinder (1973) and Oaxaca (1973), identifies the effects of characteristics and coefficients on a singular mean value but fails to account for heterogeneity. To address this limitation, researchers have combined the OB model with Conditional Quantile Regression (CQR), following the methodology of Koenker & Bassett (1978), as demonstrated by Machado and Mata (2005). While CQR-based methods shed light on disparities across different quantiles, they are constrained in isolating the contributions of individual covariates to each effect, a challenge noted by Albrecht et al. (2003) and Ganguli & Terrell (2005). UQR overcomes this by dynamically estimating the impact of covariate shifts on the unconditional quantiles of the outcome variable, using the Recentered Influence Function (RIF), enabling a distribution-wide decomposition akin to the OB model. UQR estimates offer a distinct benefit by measuring the average partial impacts of small changes in an independent variable on the respective unconditional quantile of the outcome variable. This feature significantly enhances the analysis of wage disparities between groups, such as gender, employing a method analogous to the well-known OB decomposition (Adireksombat et al., 2016; Khanna et al., 2016; Padhi et al., 2019).

Addressing the gender wage gap in urban India is a critical issue that necessitates a sophisticated understanding and identification of the diverse factors driving wage disparities. Consequently, our study employs a novel combination of the UQR approach alongside the OB-RIF decomposition, as this methodology underscores the heterogeneity in wage disparities and permits the isolation of individual factors contributing to these differences. Our research paper provides a deeper understanding of the complex dynamics driving the gender wage gap, utilizing advanced statistical tools to capture the varied impacts across the entire wage spectrum. This approach will facilitate more focused and evidence-based policy interventions aiming to address these gender wage disparities effectively.

Materials and Methods

Data

In the current study, we utilized data from the Periodic Labour Force Survey (PLFS) Schedule 10.4: Employment and Unemployment (First Visit) for the fiscal year 2022-23, conducted by the National Statistical Office (NSO) and obtained from the Ministry of Statistics and Programme Implementation (MoSPI) website. This dataset offered a rich array of cross-sectional data, capturing diverse household and individual characteristics, including but not limited to household composition, caste, religion, gender, age, educational levels, marital status, and detailed employment-related information such as types of occupation, industry sectors, and wage data. A pivotal aspect of this analysis was classifying workers into distinct categories based on their activity status delineated by the NSO. Specifically, the study delineated between two major wage employment categories, regular/salaried employees—who are engaged in work for others on a farm or non-farm basis, in both domestic and non-domestic settings, under arrangements that provide fixed salaries not contingent upon daily or periodic contract renewals—and casual wage laborers, who engage intermittently in farm or non-farm activities for others, within both household and non-household settings, with remuneration based on daily or periodic contracts. Another type of employment, self-employed, described by NSO, comprises people who operate their farm or non-farm enterprises or are engaged independently in a profession or trade and deal with profits and loss instead of wage/salary received, which complicates the formulation of a wage equation and, hence, is excluded from this research study (Das, 2018).

The research analyzed the natural logarithm of daily earnings among male and female employees within a specific demographic group in India—those aged between 15 and 59 years, representing the active labor force. The study focused on five critical points within the wage distribution: the 10th, 25th, 50th, 75th, and 90th percentiles. This approach aimed to provide a detailed insight into how various factors influence wage distribution across lower and higher ends and the median, offering a comprehensive overview of wage trends within the Indian workforce.

The study examined the impact of categorical variables such as marital status, caste affiliation, residential sector, educational attainment (general and technical), employment type, and enterprise type on wage levels. The Ministry of Labour & Employment classified occupations according to the National Occupational Classification (NCO, 2015) into four main groups: Professionals and Managers (NCO 1-2), Skilled Workers and Service Providers (NCO 3-5), Production and Craft Workers (NCO 6-8), and Elementary Occupations (NCO 9). Similarly, the National Industrial Classification (NIC, 2008) was further grouped into five major types with NIC codes: Production and Extraction (NIC 1 to 3), Infrastructure and Utilities (NIC 4 to 6), Goods and Service Distribution (NIC 7 to 9), Knowledge and Service-Based (NIC 10 to 15), and Public and Social Services (NIC 16 to 20). The analysis utilized UQR models, treating categorical variables as dummy variables, with one category as the reference for comparative purposes. This method allowed for assessing how each category influenced the wage distribution relative to the reference group.

The analysis utilized Stata v.13 statistical software on a Windows x64 platform, applying sample weights to improve the accuracy of the estimations. Before model fitting, the data was cleaned to remove missing entries where wage/salary information was unavailable for the survey's reference period. To eliminate outliers, 0.5 percent of values from both extremes of the dataset were discarded (Khanna et al., 2016). This process resulted in a refined dataset comprising 34,035 participants, with 7,621 female and 26,414 male responses. Such meticulous data preparation ensured that the study's findings offered reliable insights into the factors affecting wage distribution among India's active labor force. The refined dataset comprised 34,035 participants, with 7,621 female and 26,414 male responses. This rigorous approach ensured that the findings provided reliable insights into the factors affecting wage distribution among India's active labor force.

Segregation Indices

Segregation indices are crucial tools in labor economics for measuring the extent of occupational segregation between different groups, such as by gender or race. These indices help quantify how such segregation contributes to wage disparities by indicating how groups are unevenly distributed across occupations, with higher values signaling greater segregation.

Gini Index

Also known as the Gini Coefficient, it is a statistical measure purposed to indicate the income or wealth distribution disparity in a given country. It is the primary metric for assessing inequality, with values ranging from 0 to 1. A value of 0 indicates perfect equality, while 1 signifies complete inequality. The Gini coefficient can be calculated as:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} |x_i - x_j|}{2n^2\bar{x}} \quad (1)$$

In this formula, G denotes the Gini coefficient, n represents the people in the population, x_i and x_j are the incomes of individuals i and j, respectively, and $\bar{x}$ is the average income across the population.

Dissimilarity Index

The Index of Dissimilarity, also known as the Dissimilarity Index, quantifies the disparities in distribution between two distinct groups. This metric is instrumental in assessing the extent of occupational segregation and the disparity in earnings between genders by revealing the proportion of individuals from one group that must switch occupations to mirror the occupational distribution of the other group. The formula is expressed as:

$$D = \frac{1}{2}\sum_{i=1}^{k}\left|\frac{w_i}{W} - \frac{m_i}{M}\right| \quad (2)$$

Here, M and W represent the total number of males and females in all occupations; m_i and w_i represent number of males and females in the i^{th} occupation, and k is the total number of occupations.

The index D can range from 0 to 1, with 0 signifying the absence of segregation (an ideal equal distribution between males and females across various occupations) and 1 signifying absolute segregation.

Unconditional Quantile Regression (UQR) Model

Our research employs the UQR model to explore the influence of worker attributes on income distribution, as opposed to CQR, which concentrates on particular quantiles of the outcome variable's distribution. UQR delivers a comprehensive perspective on how independent factors impact overall inequality by assessing their effects throughout the entire range of the outcome variable. This technique is advantageous for comprehending the diverse effects of elements like policy modifications or economic transformations on income distribution, thereby facilitating the creation of fairer policies.

The fundamental concept of UQR is based on the use of influence functions (IFs), which measure the impact of a single data point on a given distributional statistic. UQR utilizes the RIF for a chosen quantile (θ) to assess how individual changes in covariates affect the overall conditional distribution of the resultant variable, leading to the term "RIF regression," as described by Rios-Avila (2020). The estimation process is split into two separate phases. First, the RIF for the θ^{th} quantile of the dependent variable is determined, creating a new variable reflecting the contribution of each observation to that quantile. In the second step, an OLS regression is performed where this RIF variable is regressed on the independent variables (covariates). The last phase of this procedure entails assessing the marginal impacts of each covariate across the full range of the outcome variable's quantiles. This approach provides a more in-depth understanding of the covariates' effects compared to traditional conditional quantile regression methods.

The RIF is calculated by reintegrating the statistic into the IF, representing how an observation has on that distributional statistic. This calculation forms the basis of the RIF:

$$\mathrm{RIF}(w,q_\theta) = q_\theta + \mathrm{IF}(w,q_\theta) = q_\theta + \frac{[\theta - I\{w \le q_\theta\}]}{f_w(q_\theta)} \quad (3)$$

In this context, w denotes earnings, and q_θ represents the θ^{th} quantile of the unconditional distribution of earnings. The indicator function is denoted by I{.}, and f_w symbolizes the density of the marginal distribution of earnings.

The UQR or RIF regression framework is set up by asserting the conditional expectation of the RIF as a function of specific explanatory variables, X, in this way:

$$E[\mathrm{RIF}(w,q_\theta)|X] = X\beta \quad (4)$$

Here, β is the marginal impact of X on the θ^{th} quantile, which is calculable via OLS by substituting the RIF estimate for the dependent variable. The RIF is computed by incorporating the model quantile. $\widehat{q_\theta}$ and the empirical density, $\widehat{f_w}(q_\theta)$, calculated using kernel techniques into equation (3).

Oaxaca-Blinder Recentered Influence Function (OB-RIF) Decomposition

This methodology provides an advanced analytical framework for examining significant shifts observed in a statistical measure of distribution. This method breaks down the analysis into two primary components:

Component of Explained Variation (Endowment or Structural Effect): This aspect highlights the part of the wage disparity that can be traced back to the variations in noticeable attributes or endowments within the studied groups. It seeks to determine how these differences can account for the observed wage gap.

Component of Unexplained Variation (Discrimination or Compositional Effect): This aspect addresses the segment of the wage gap that differences in observable attributes cannot explain. It highlights the existence of unequal pay that could stem from various sources, including discriminatory practices, unmeasured abilities, or other hidden factors.

The approach employs coefficients derived from UQR or RIF regression analyses, particularly on quantiles. In this context, the regression coefficients of the RIF play a pivotal role in shedding light on the impacts on each group being examined. These coefficients are essential for comprehensively examining how attributes and composition affect wage differences. They facilitate a detailed investigation into the association between alterations in the distributional statistic, shifts in the returns to covariates, and changes in the distribution of these covariates among various groups. The RIF regression coefficients for the groups, denoted as T = male and female, are calculated using the following formula:

$$\widehat{\beta}_{T,\theta} = \left(\sum_{i \in T} X_{Ti}.X'_{Ti}\right)^{-1} \sum_{i \in T} \widehat{\mathrm{RIF}}(w_{Ti}, q_{T\theta}).X_i \quad (5)$$

The formula for the overall decomposition of any unconditional quantile θ is:

$$\widehat{\Delta}^{\theta}_{\mathrm{Total}} = \overline{X_2}\left(\widehat{\beta}_{2,\theta} - \widehat{\beta}_{1,\theta}\right) + (\overline{X_2} - \overline{X_1})\widehat{\beta}_{1,\theta}$$
$$\widehat{\Delta}^{\theta}_{\mathrm{Total}} = \widehat{\Delta}^{\theta}_{\mathrm{Explained}} + \widehat{\Delta}^{\theta}_{\mathrm{Unexplained}} \quad (6)$$

The OB-RIF decomposition method stands out from other decomposition approaches, like the Machado-Mata method, by providing a more granular analysis of structure and composition effects. This distinctive aspect allows for the dissection of these effects to reveal the distinct contributions from each covariate, making it more aligned with the thorough OB Decomposition. Thus, this approach enhances explanatory power by pinpointing the effect of each covariate on structure and composition effects, providing deeper insight into the elements driving changes in distributional statistics (Khanna et al., 2016). To assess the individual influence of each covariate, it is possible to express the two components in equation (6) in a more detailed manner:

$$\widehat{\Delta}^{\theta}_{\text{Explained}} = \sum_{k=1}^{K} (\overline{X}_{2k}-\overline{X}_{1k})\widehat{\beta}_{1k,\theta} \quad (7)$$

$$\widehat{\Delta}^{\theta}_{\text{Unexplained}} = \sum_{k=1}^{K} \overline{X}_{2k}\left(\widehat{\beta}_{2k,\theta}-\widehat{\beta}_{1k,\theta}\right) \quad (8)$$

Results

Gender Wage Disparity and Segregation

The number of male workers in the population was 52,013,136 (76.94 percent), substantially higher than that of female workers at 15,585,648 (23.06 percent). The average daily wage for male workers was Rs. 843.12, while for female workers, it was Rs. 722.82. This shows that, on average, females are paid less than males for their labor. When the wages of both genders are pooled together, the average daily salary comes to Rs. 815.39, which is closer to the male average than the female average, reflecting the higher wages of male workers. The difference in participation in the workforce might also have contributed to the wage disparity.

The study found that the Dissimilarity Index was 0.2234, indicating that approximately 22.34 percent of female workers would have needed to move to higher-paying occupations or roles to achieve the same wage distribution as male workers. This index measured occupational segregation and pointed to a moderate level of segregation between the types of occupations typically held by males and females.

The overall Gini Index was determined to be 0.42, reflecting moderate income inequality among all urban workers. The Gini Index stood at 0.394 for male workers, which was lower than the overall index, suggesting slightly less income inequality within the male urban worker population than the overall urban workforce. Conversely, the Gini Index for female workers was 0.49, higher than the overall and male indexes. This indicated a higher level of income inequality among female urban workers compared to their male counterparts and the urban workforce in general.

Therefore, a distinct gender wage gap existed in India's urban regions, where the average income of male employees exceeded that of their female counterparts. The higher Gini Index for females suggested that income inequality was more pronounced among female workers. The Dissimilarity Index highlighted occupational segregation as a significant factor contributing to the wage gap, with a considerable proportion of females needing to change occupations to achieve wage parity with males.

Analyzing Wage Determinants through UQR Modeling

Tables 1 and 2 display the UQR modeling results for male and female employees, which used the natural logarithm of daily wages for the urban sector as the variable of interest. Interpreting categorical variables within the UQR framework is notably challenging due to the complex nature of Unconditional Partial Effects (UPE) and the standard RIF regression technique. This technique assesses the impact that slight variations in the distribution of independent variables exert on the dependent variable. Hence, it is critical to note that interpreting the categorical variables' coefficients as indicative of binary shifts (from 0 to 1) is methodologically flawed. Such an interpretation erroneously suggests a complete redistribution of the categorical variable, transitioning from a state of non-occurrence to universal prevalence within the dataset. This misinterpretation could lead to substantial biases in the estimation of UPE. A more methodologically sound approach involves assessing the UPE by considering deviations from the mean unconditional dependent variable distribution. This alternative technique provides a more accurate insight into the effects of changes in categorical variables on wage distribution, free from the distortions linked to binary transformations. For instance, a rise of 10 percentage points in the proportion of a specific category within the population would result in a wage adjustment calculated as [(Estimate/Avg. RIF) x 0.1 x 100 percent]. Here, the "Avg. RIF" represents the average value of the RIFs calculated for a specific statistic across different groups or conditions within the data. Our study adopts this refined approach to interpret the influence of a 10 percent point increase in workforce composition on the natural logarithmic values of daily wages.

The participants' ages were categorized into three groups: 15 to 29 years, 30 to 44 years, and 45 to 59 years, with the latter as the reference category. Analysis revealed significant negative coefficients among male and female workers for both younger age groups. Specifically, a 10 percent point rise in the proportion of workers within the 15 to 29 and 30 to 44 age groups was significantly correlated with wage decreases ranging from 0.16 percent to 0.57 percent and 0.08 percent to 0.38 percent, respectively, relative to the reference group. This trend was consistent across genders, with female workers in these age groups experiencing significant wage decreases of 0.28 percent to 0.53 percent (15-29 years) and a reduction of 0.17 percent to 0.28 percent (30-44 years), except at median wage compared to the reference group. These findings indicated a negative association between the participation of younger workers and salaries for both male and female workers across various wage percentiles, with the magnitude of the effect varying by gender and age group.

Significant disparities were observed in wage distribution across caste affiliations among male workers. Scheduled Caste (SC) and Scheduled Tribe (ST) social groups consistently negatively impacted wages throughout the distribution compared to the reference group. Conversely, Other Backward Class (OBC) workers only showed statistically significant wage effects in the higher percentiles (75th and 90th). A 10 percent increase in the proportion of ST workers correlated with a wage decline ranging from 0.22 percent to 0.15 percent in the lower percentiles and 0.22 percent at the 90th percentile. SC workers experienced a wage penalty ranging from 0.10 percent to 0.21 percent across the wage distribution. Interestingly, OBC males only faced a significant wage penalty at the median (0.08 percent) and 90th percentile (0.16 percent). Female workers exhibited a different pattern, with OBC and SC females showing significant wage effects at higher percentiles (75th and 90th). SC females encountered the most substantial wage penalty (0.44 percent to 0.32 percent), followed by OBC females (0.38 percent to 0.31 percent) at the upper percentiles. These findings highlighted the complex relationship between caste affiliation and wage distribution in India and the disparities between male and female workers across the wage spectrum.

While SC and ST workers consistently faced wage penalties, the effects on OBC workers were more nuanced, primarily affecting those in higher wage percentiles. The data notably revealed a significant wage penalty for SC females, even in the highest earning brackets.

Table 1 UQR model for urban sector male workers in India

Independent Variables	**percentiles**				
	10th	**25th**	**50th**	**75th**	**90th**
Age *(45 to 59 years)*					
15 to 29 years	-0.09*** (0.02)	-0.12*** (0.02)	-0.26*** (0.02)	-0.45*** (0.03)	-0.42*** (0.03)
30 to 44 years	0.05*** (0.01)	0.02 (0.01)	-0.08*** (0.01)	-0.21*** (0.02)	-0.28*** (0.03)
Social Group *(Others)*					
ST	-0.09*** (0.02)	-0.12*** (0.02)	-0.26*** (0.02)	-0.45*** (0.03)	-0.42*** (0.03)
SC	0.05*** (0.01)	0.02 (0.01)	-0.08*** (0.01)	-0.21*** (0.02)	-0.28*** (0.03)
OBC	-0.09*** (0.02)	-0.12*** (0.02)	-0.26*** (0.02)	-0.45*** (0.03)	-0.42*** (0.03)
Marital Status *(Never Married)*					
Currently Married	0.18*** (0.02)	0.13*** (0.02)	0.12*** (0.02)	0.10*** (0.02)	0.09*** (0.02)
Widow	-0.03 (0.11)	0.03 (0.06)	-0.05 (0.06)	-0.11 (0.10)	-0.09 (0.09)
Divorced	-0.23* (0.11)	-0.10 (0.06)	0.02 (0.06)	0.04 (0.08)	0.08 (0.09)
General Education *(Illiterate)*					
Without Formal Schooling	-0.06 (0.24)	0.09 (0.14)	-0.34 (0.18)	-0.25* (0.10)	-0.18* (0.08)
Up to Primary	-0.03 (0.04)	0.02 (0.03)	0.04 (0.03)	0.01 (0.02)	0.03* (0.01)
Middle School	0.02 (0.04)	0.09** (0.03)	0.16*** (0.03)	0.11*** (0.03)	0.05** (0.02)
Secondary	0.13*** (0.04)	0.16*** (0.03)	0.26*** (0.03)	0.13*** (0.03)	0.01 (0.02)
Higher-Secondary	0.13** (0.04)	0.21*** (0.03)	0.32*** (0.04)	0.19*** (0.04)	0.04 (0.03)
Graduate	0.26*** (0.04)	0.35*** (0.03)	0.51*** (0.04)	0.58*** (0.04)	0.18*** (0.04)
Postgraduate and above	0.29*** (0.04)	0.36*** (0.03)	0.56*** (0.04)	0.87*** (0.06)	0.64*** (0.07)
Technical Education (*No technical education*)					
Degree	0.01 (0.01)	0.02 (0.01)	0.08*** (0.02)	0.63*** (0.05)	0.79*** (0.09)
Diploma/ Certificate	0.01 (0.02)	0.01 (0.02)	-0.03 (0.04)	0.14* (0.05)	0.26*** (0.07)
Type of Worker *(Casual Wage Worker)*					
Regular/ Salaried Worker	-0.06 (0.03)	-0.31*** (0.02)	-0.01 (0.03)	-0.14*** (0.02)	-0.09*** (0.02)
Type of Enterprise *(Public/Private and Others)*					
Public	-0.05** (0.02)	0.01 (0.02)	0.14*** (0.02)	0.88*** (0.04)	0.56*** (0.05)
Private	-0.22*** (0.02)	-0.23*** (0.02)	-0.29*** (0.02)	-0.33*** (0.03)	-0.12*** (0.02)
Occupation *(Elementary Occupations)*					
Professionals and Managers	0.06 (0.03)	0.19*** (0.03)	0.50*** (0.03)	1.06*** (0.05)	0.80*** (0.05)
Skilled Workers and Service Providers	0.00 (0.03)	0.09*** (0.02)	0.25*** (0.02)	0.24*** (0.03)	-0.02 (0.02)
Production and Craft Workers	0.13*** (0.03)	0.16*** (0.02)	0.31*** (0.02)	0.15*** (0.02)	0.04** (0.01)
Industry *(Public and Social Services)*					
Production and Extraction	0.09*** (0.03)	0.09*** (0.02)	0.13*** (0.02)	0.30*** (0.04)	0.24** (0.04)
Infrastructure and Utilities	0.30*** (0.04)	0.25*** (0.03)	0.33*** (0.03)	0.35*** (0.04)	0.22*** (0.04)
Goods and Services	0.06 (0.03)	0.04 (0.02)	0.09*** (0.02)	0.25*** (0.03)	0.25*** (0.03)
Knowledge and Service-Based	0.10*** (0.02)	0.11*** (0.02)	0.21*** (0.02)	0.58*** (0.04)	0.56*** (0.05)
Intercept	5.55*** (0.06)	5.95*** (0.05)	5.86*** (0.05)	6.26*** (0.06)	7.18*** (0.05)
Avg. RIF	5.76	6.03	6.40	6.87	7.48
R^2	0.09	0.19	0.33	0.52	0.35

** for p<.05, ** for p<.01, *** for p<.001*
Standard errors are presented in parentheses, along with coefficient values.
Reference categories for independent variables are indicated in parentheses.

Table 2 UQR model for urban sector female workers in India

Independent Variables	percentiles				
	10th	**25th**	**50th**	**75th**	**90th**
Age *(45 to 59 years)*					
15 to 29 years	-0.14* (0.07)	-0.16** (0.05)	-0.16*** (0.04)	-0.48*** (0.09)	-0.40*** (0.08)
30 to 44 years	-0.09* (0.04)	-0.10* (0.04)	-0.07* (0.03)	-0.18** (0.06)	-0.21*** (0.05)
Social Group *(Others)*					
ST	-0.02 (0.09)	-0.06 (0.09)	-0.06 (0.06)	-0.05 (0.07)	-0.15* (0.06)
SC	-0.04 (0.06)	-0.08 (0.05)	-0.06 (0.04)	-0.30*** (0.06)	-0.24*** (0.05)
OBC	0.01 (0.05)	-0.00 (0.04)	-0.02 (0.03)	-0.26*** (0.05)	-0.23*** (0.06)
Marital Status *(Never Married)*					
Currently Married	0.08 (0.06)	0.07 (0.04)	0.07 (0.04)	0.15 (0.09)	0.24** (0.08)
Widow	0.24** (0.08)	0.17** (0.07)	0.14* (0.06)	0.08 (0.10)	0.10 (0.09)
Divorced	0.27* (0.13)	0.21 (0.13)	0.04 (0.10)	0.11 (0.12)	0.09 (0.10)
General Education *(Illiterate)*					
Without Formal Schooling	1.03*** (0.11)	1.34*** (0.12)	0.09 (0.25)	0.04 (0.08)	0.04 (0.06)
Up to Primary	0.12 (0.09)	0.14* (0.07)	0.05 (0.05)	0.06 (0.03)	0.04 (0.02)
Middle School	0.38*** (0.09)	0.28*** (0.07)	0.13* (0.05)	-0.03 (0.04)	0.02 (0.03)
Secondary	0.56*** (0.10)	0.50*** (0.08)	0.25*** (0.06)	-0.12* (0.06)	-0.05 (0.03)
Higher-Secondary	0.70*** (0.09)	0.67*** (0.08)	0.52*** (0.08)	0.03 (0.08)	-0.01 (0.05)
Graduate	0.86*** (0.10)	0.98*** (0.08)	0.97*** (0.07)	0.74*** (0.10)	0.16* (0.07)
Postgraduate and above	0.97*** (0.10)	1.08*** (0.08)	1.16*** (0.07)	1.14*** (0.14)	0.35*** (0.11)
Technical Education *(No technical education)*					
Degree	0.12*** (0.03)	0.07* (0.03)	0.18*** (0.04)	0.83*** (0.12)	0.70*** (0.14)
Diploma/ Certificate	0.17*** (0.03)	0.15*** (0.03)	0.10* (0.04)	0.23 (0.15)	0.33* (0.14)
Type of Worker *(Casual Wage Worker)*					
Regular/ Salaried Worker	-0.14 (0.12)	-0.24* (0.10)	-0.18** (0.07)	0.07 (0.06)	-0.04 (0.04)
Type of Enterprise *(Public/Private and Others)*					
Public	0.00 (0.05)	0.03 (0.04)	-0.01 (0.04)	0.62*** (0.10)	0.31*** (0.09)
Private	-0.17** (0.06)	-0.22*** (0.05)	-0.38*** (0.04)	-0.51*** (0.08)	-0.24*** (0.06)
Occupation *(Elementary Occupations)*					
Professionals and Managers	-0.08 (0.09)	0.07 (0.07)	0.32*** (0.06)	0.95*** (0.10)	0.46*** (0.08)
Skilled Workers and Services Providers	-0.04 (0.08)	-0.02 (0.07)	0.12** (0.05)	-0.09 (0.05)	-0.12*** (0.03)
Production and Craft Workers	-0.30* (0.14)	-0.03 (0.11)	0.10 (0.08)	0.02 (0.07)	-0.00 (0.04)
Industry *(Public and Social Services)*					
Production and Extraction	0.58*** (0.07)	0.46*** (0.07)	0.15** (0.06)	0.20* (0.10)	0.05 (0.06)
Infrastructure and Utilities	0.81*** (0.10)	0.91*** (0.09)	0.88*** (0.10)	0.32** (0.10)	0.05 (0.06)
Goods and Services	0.47*** (0.06)	0.49*** (0.06)	0.28*** (0.05)	0.39*** (0.07)	0.28*** (0.05)
Knowledge and Service-Based	0.27*** (0.05)	0.32*** (0.04)	0.33*** (0.04)	1.01*** (0.09)	0.62*** (0.09)
Intercept	4.55*** (0.16)	5.03*** (0.13)	5.54*** (0.10)	6.17*** (0.17)	7.31*** (0.13)
Avg. RIF	5.11	5.53	6.01	6.89	7.50
R^2	0.14	0.27	0.44	0.53	0.28

** for p<.05, ** for p<.01, *** for p<.001*
Standard errors are presented in parentheses, along with coefficient values.
Reference categories for independent variables are indicated in parentheses.

Marital status was also identified as having a consistent and statistically significant favorable influence on the earnings of male employees throughout all quantiles. The most significant effect was noted at the 10th percentile, where wages increased by 0.31 percent, and this effect gradually decreased to 0.11 percent at the 90th percentile. On the other hand, marital status's effect on the wages of female employees was only significant at the 90th percentile, which resulted in a 0.32 percent wage increase. The marital statuses of being widowed, divorced, or separated did not significantly affect male wages at any quantile. However, being widowed was associated with a wage increase of approximately 0.48 percent to 0.23 percent for females from the 10th to 50th percentile. Divorce (or separation) was significantly associated with a 0.40 percent wage increase for males and a 0.52 percent increase for females at the 10th percentile, with the effect becoming insignificant at higher percentiles. These results indicated that marriage is associated with increased earnings for both genders, though more steadily and strongly for males throughout the wage spectrum.

The study showed a consistent and statistically significant rise in the effect of education on earnings for male employees in every educational group, as measured by log income, spanning from the 10th to the 90th percentiles, except those without formal schooling. Specifically, within the "postgraduate and above" group, it was noted that the coefficient for salary growth escalated from 0.29 (0.50 percent) at the 10th percentile to 0.56 (0.87 percent) at the 50th percentile and then to 0.87 (1.26 percent) at the 75th percentile. At the same time, the impact of higher education on salaries also proved to be substantially positive for female workers. For females in the "postgraduate and above" category, the coefficients demonstrated a marked rise from 0.97 (1.89 percent) at the 10th percentile to 1.16 (1.93 percent) at the median and reached 1.14 (1.66 percent) at the 75th percentile. Notably, female workers without formal education also experienced a significant wage increase at the lower percentiles, with an approximate rise of 2.03 percent to 2.43 percent at the 10th and 25th percentiles, respectively. These figures could indicate a higher proportion of female workers in roles that did not necessitate formal education. Thus, higher general education levels (graduate and postgraduate) led to more significant wage gains for both genders, with females generally experiencing more significant percentage increases than males, especially in general education. Regarding technical education, a significant impact for male degree workers started from the median (0.12 percent). It peaked at the 90th percentile (1.05 percent), whereas, for female workers, it was significantly positive across all quantiles, particularly strongest at the 75th percentile (1.21 percent). For the urban sector workers with diplomas or certificates in technical education, the male workers had slightly lesser positive impacts only in higher quantiles (0.20 percent at the 75th and 0.35 percent at the 90th percentiles, respectively). For female urban workers, the diploma or certificate in technical education led to almost consistent positive impacts across all quantiles, with the most significant being at the ends of the wage distribution, i.e. 0.33 percent at 10th and 0.43 percent at 90th percentiles, respectively. This showed that technical education had benefited females more than males, especially degree holders, and had significantly boosted wages in the upper quantiles for both genders, suggesting it had helped workers achieve higher earnings.

For male employees, holding a regular or salaried position was linked to a statistically significant decrease in wages across the majority of percentiles when compared to casual wage workers, with reductions varying from 0.52 percent at the 25th percentile to 0.12 percent at the 90th percentile. Female workers also experienced a significantly negative effect at the median of the wage distribution, 0.43 percent at the 25th percentile and 0.31 percent at the 50th percentile.

Male workers in public enterprises were found to have significantly higher wages than those in other or mixed types of enterprises across all percentile levels, with a wage premium ranging from approximately 0.22 percent at the 50th percentile to 0.76 percent at the 90th percentile. Conversely, female workers in public enterprises encountered an insignificant effect on wages from the 10th to 50th percentile and only saw a positive wage effect at the 75th (0.90 percent) and 90th (0.42 percent) percentiles. Private enterprise workers, regardless of gender, consistently earned lower wages compared to workers in other enterprise types across all quantile levels, with male workers experiencing a wage disadvantage ranging from 0.39 percent to 0.48 percent and female workers from 0.33 percent to 0.74 percent. However, this effect was comparatively lesser at the highest 90th percentile of the wage distribution. These patterns suggested that public enterprises offered higher wages and potentially more stability, particularly for male and high-earning female workers. In comparison, private enterprises were linked to reduced salaries for both males and females.

Male workers in most occupational categories earned significantly more than those in elementary occupations across nearly all wage levels, with the wage gap increasing at higher quantiles. For instance, professionals and managers earned 1.55 percent more at the 75th percentile but 0.31 percent at the 25th. Male skilled workers and service providers saw a wage advantage ranging from 0.14 percent to 0.35 percent from the 25th to 75th percentile. Similarly, male workers in production and craft occupations enjoyed a wage premium across the wage distribution, about 0.22 percent to 0.05 percent. Female professionals and managers also earned more than those in elementary occupations from the median to the upper wage levels, with the wage gap expanding at higher quantiles (1.38 percent more at the 75th percentile compared to 0.53 percent at the 50th). However, wage gaps for female skilled workers, service providers, and production and craft workers were inconsistent compared to elementary occupations. These findings indicated a complex interplay between occupation and gender in determining wage distributions.

The study also assessed the impact of industry type on the wages of male and female employees and revealed significant findings. In the Production and Extraction industry, an increase in the proportion of male workers by 10 percent points was associated with a wage increase ranging from 0.16 percent to 0.32 percent. In contrast, a similar increase in female workers correlated with a wage increase from 1.14 percent to 0.83 percent for wages below the median. The Infrastructure and Utility industry showed that male employees experienced wage increases between 0.52 percent and 0.29 percent, whereas female employees saw more pronounced increases, ranging from 1.59 percent to 0.46 percent. In the Goods and Services industry, wage impact varied by gender and wage distribution; male employees observed wage increases from

0.14 percent to 0.33 percent above the median wage, and female employees experienced increases from 0.93 percent to 0.37 percent. The Knowledge and Service-based industry demonstrated a significantly positive relationship with wages for both genders; male wages increased between 0.17 percent and 0.75 percent, while female wages ranged from 0.53 percent to 0.83 percent, indicating a stronger positive wage response for female in knowledge-intensive and service-oriented industries compared to their male counterparts. These findings suggested that industry type played a crucial role in influencing wage disparities between genders, with female employees generally benefitted more in industries characterized by higher knowledge intensity and service orientation.

The R^2 value reflected how well independent variables explained wage variation across different quantiles. For male workers, R^2 values ranged from 0.09 to 0.52, indicating an increasing explanatory power from the 10th to the 75th percentile. This suggested that the model explained wage variation among higher earners more effectively. Female workers showed a similar pattern, with R^2 values ranging from 0.14 to 0.53 from the 10th to the 75th percentile. Hence, the R^2 values indicated that the selected independent variables in the UQR models were more predictive of wages at the upper end of the wage distribution for employees of both genders in India's urban areas.

Gender Wage Gap using OB-RIF Decomposition

The analysis of OB-RIF Decomposition, as depicted in Table 3, revealed significant findings regarding the wage disparity between genders within the urban workforce. The results showed a persistent and significant difference in wages favoring males in the bottom half of the wage scale, especially at the 10th, 25th, and 50th percentiles, where the disparity varied between 0.65, 0.50, and 0.39, respectively. This implied that the wage disparity was more significant at the bottom of the wage scale.

However, at the 75th and 90th percentiles, the difference in earnings between the genders was not statistically significant, indicating that the wage gap diminished and eventually reversed at the upper end of the wage spectrum. The explained component contributed positively to the wage gap at lower percentiles: 0.15 at the 10th, 0.18 at the 25th, and 0.07 at the 50th percentiles, respectively. This suggests that differences in characteristics between the two genders contributed to the wage disparity. At higher percentiles (75th and 90th), the explained component became negative (-0.24 and -0.08), indicating that these characteristics favored females or were more advantageous to females in higher wage distributions. The unexplained component remained positive across all percentiles but decreased from 0.50 at the 10th percentile to 0.33 at the median and 0.08 at the 90th percentile. This pattern suggested that females either possessed more highly rewarded characteristics at higher wage levels or faced less discrimination. Conversely, a more significant unexplained component indicated greater discrimination against females at lower wage levels.

Figure 1, a visual representation of the wage disparity between males and females across different percentiles of the wage distribution, highlights the explained and unexplained components of the differential and concurs with the results obtained in Table 3.

Table 3 OB-RIF decomposition of the gender wage differential in urban sector workers of India

	percentiles				
Components	**10th**	**25th**	**50th**	**75th**	**90th**
Male Group	5.76*** (0.01)	6.03*** (0.01)	6.40*** (0.01)	6.92*** (0.01)	7.52*** (0.01)
Female Group	5.11*** (0.02)	5.53*** (0.02)	6.01*** (0.02)	6.89*** (0.04)	7.53*** (0.03)
Difference	0.65*** (0.02)	0.50*** (0.02)	0.39*** (0.02)	0.02 (0.04)	-0.01 (0.03)
Explained	0.15*** (0.03)	0.18*** (0.02)	0.07** (0.02)	-0.24*** (0.04)	-0.08*** (0.02)
Unexplained	0.50*** (0.03)	0.32*** (0.03)	0.33*** (0.02)	0.26*** (0.03)	0.07** (0.03)

** for p<.05, ** for p<.01, *** for p<.001*
Standard errors are presented in parentheses, along with coefficient values.

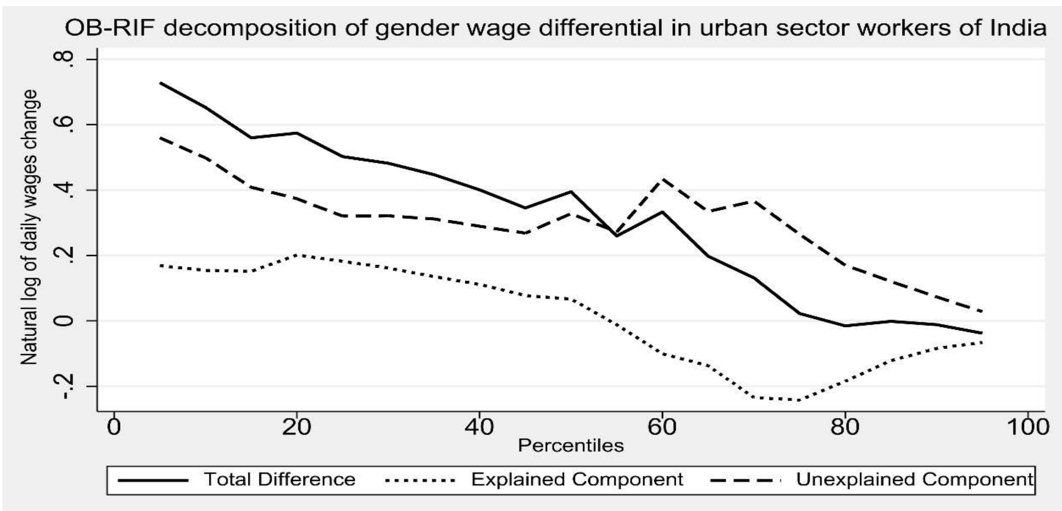

Figure 1 OB-RIF decomposition of gender wage differential in urban sector workers of India

The solid black line in the figure illustrates the overall wage gap between males and females. It consistently stayed below zero across all percentiles, indicating that, on average, females earned less than males in the urban region. This discrepancy was more significant at the bottom of the wage distribution and appeared to diminish as one progressed to the higher percentiles. The dot-dashed line in the figure represents the explained portion of the wage disparity, which remained relatively level and near zero, indicating that the observable attributes did not explain much of the wage difference. The dotted line in the figure symbolizes the unexplained portion of the wage disparity, which remained more significant than the explained portion, particularly at the lower percentiles. This suggested that these unaccounted factors significantly contributed to the wage gap.

The OB-RIF Decomposition analysis provided further insights into the factors contributing to wage disparities across different wage distributions, distinguishing between explained (composition effect) and unexplained (structure effect) components, as detailed in Tables 4 and 5, respectively. Age, particularly in the 15–29-year age group, significantly influenced the explained component, suggesting that age-related differences in human capital and experience partly account for the observed wage gap. Marital status, focusing on married or widowed individuals, and education, with levels ranging from middle school to postgraduate qualifications, were significant factors in explaining wage differences between genders.

Table 4 Explained Component (Characteristic Effect) from OB-RIF decomposition of the gender wage differential in urban sector workers of India.

Independent Variables	percentiles 10th	25th	50th	75th	90th
Age *(45 to 59 years)*					
15 to 29 years	-0.01 (0.00)	-0.01* (0.00)	-0.01** (0.00)	-0.02*** (0.01)	-0.02*** (0.00)
30 to 44 years	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Social Group *(Others)*					
ST	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00* (0.00)
SC	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
OBC	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.01** (0.00)	-0.01** (0.00)
Marital Status *(Never Married)*					
Currently Married	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.01)	0.02* (0.01)
Widow	-0.03** (0.01)	-0.02** (0.01)	-0.01* (0.01)	-0.01 (0.01)	-0.01 (0.01)
Divorced	-0.00* (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
General Education *(Illiterate)*					
Without Formal Schooling	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Up to Primary	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Middle School	0.03*** (0.01)	0.02*** (0.01)	0.01* (0.00)	-0.00 (0.00)	0.00 (0.00)
Secondary	0.04*** (0.01)	0.03*** (0.01)	0.01*** (0.00)	-0.01* (0.00)	-0.00 (0.00)
Higher Secondary	0.03*** (0.01)	0.03*** (0.00)	0.02*** (0.00)	0.00 (0.00)	-0.00 (0.00)
Graduate	-0.03** (0.01)	-0.03** (0.01)	-0.03** (0.01)	-0.03** (0.01)	-0.00 (0.00)
Postgraduate and above	-0.07*** (0.01)	-0.08*** (0.01)	-0.08*** (0.01)	-0.09*** (0.01)	-0.02** (0.01)
Technical Education (*No technical education***)**					
Degree	-0.00** (0.00)	-0.00* (0.00)	-0.01*** (0.00)	-0.03*** (0.01)	-0.02*** (0.01)
Diploma/ Certificate	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Type of Worker *(Casual Wage Worker)*					
Regular/ Salaried Worker	0.01 (0.01)	0.02** (0.01)	0.02** (0.01)	-0.01 (0.01)	0.00 (0.00)
Type of Enterprise *(Public/Private and Others)*					
Public	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.03*** (0.01)	-0.01** (0.00)
Private	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.01)	-0.00 (0.00)
Occupation *(Elementary Occupations)*					
Professionals and Managers	0.01 (0.01)	-0.01 (0.01)	-0.04*** (0.01)	-0.15*** (0.02)	-0.06*** (0.01)
Skilled Workers and Service Providers	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Production and Craft Workers	-0.07** (0.02)	-0.01 (0.02)	0.02 (0.01)	0.00 (0.02)	0.00 (0.01)
Industry *(Public and Social Services)*					
Production and Extraction	0.06*** (0.01)	0.04*** (0.01)	0.01** (0.00)	0.02* (0.01)	0.00 (0.01)
Infrastructure and Utilities	0.11*** (0.01)	0.12*** (0.01)	0.10*** (0.01)	0.05** (0.01)	0.01 (0.01)
Goods and Services	0.07*** (0.01)	0.07*** (0.01)	0.04*** (0.01)	0.06*** (0.01)	0.04*** (0.01)
Knowledge and Service-Based	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.01)	0.00 (0.01)

** for p<.05, ** for p<.01, *** for p<.001*
Standard errors are presented in parentheses, along with coefficient values.
Reference categories for independent variables are indicated in parentheses.

Table 5 Unexplained Component (Coefficient Effect) from OB-RIF decomposition of the gender wage differential in urban sector workers of India

Independent Variables	**10th**	**25th**	**50th**	**75th**	**90th**
			percentiles		
			Age *(45 to 59 years)*		
15 to 29 years	0.02 (0.02)	0.01 (0.02)	-0.03* (0.01)	0.04 (0.03)	-0.03 (0.03)
30 to 44 years	0.06** (0.02)	0.05** (0.02)	-0.01 (0.02)	0.00 (0.03)	-0.06* (0.03)
			Social Group *(Others)*		
ST	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
SC	-0.00 (0.01)	0.01 (0.01)	-0.00 (0.01)	0.03** (0.01)	0.01 (0.01)
OBC	-0.01 (0.02)	0.01 (0.02)	0.03* (0.01)	0.11*** (0.03)	0.03 (0.03)
			Marital Status *(Never Married)*		
Currently Married	0.07 (0.04)	0.04 (0.03)	0.04 (0.03)	-0.04 (0.08)	-0.08 (0.06)
Widow	-0.00* (0.00)	-0.00 (0.00)	-0.00* (0.00)	-0.00 (0.00)	-0.00 (0.00)
Divorced	-0.00** (0.00)	-0.00* (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
			General Education *(Illiterate)*		
Without Formal Schooling	-0.00* (0.00)	-0.00** (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Up to Primary	-0.02 (0.02)	-0.02 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.00 (0.00)
Middle School	-0.08*** (0.02)	-0.04* (0.02)	0.01 (0.01)	0.04** (0.01)	0.01 (0.01)
Secondary	-0.06*** (0.01)	-0.05*** (0.01)	0.00 (0.01)	0.04*** (0.01)	0.01 (0.01)
Higher Secondary	-0.07*** (0.01)	-0.06*** (0.01)	-0.02* (0.01)	0.02* (0.01)	0.01 (0.01)
Graduate	-0.17*** (0.03)	-0.17*** (0.02)	-0.11*** (0.02)	-0.05 (0.03)	0.02 (0.02)
Postgraduate and above	-0.06*** (0.01)	-0.06*** (0.01)	-0.04*** (0.01)	-0.03** (0.01)	0.03*** (0.01)
			Technical Education (*No technical education*)		
Degree	-0.01*** (0.00)	-0.00 (0.00)	-0.01* (0.00)	-0.03** (0.01)	0.02 (0.01)
Diploma/ Certificate	-0.01*** (0.00)	-0.01*** (0.00)	-0.01* (0.00)	-0.01 (0.01)	0.00 (0.01)
			Type of Worker *(Casual Wage Workers)*		
Regular/ Salaried Workers	0.07 (0.08)	-0.05 (0.07)	0.13** (0.05)	-0.13* (0.06)	-0.05 (0.03)
			Type of Enterprise *(Public/Private and Others)*		
Public	-0.01 (0.01)	-0.00 (0.01)	0.02*** (0.01)	0.02 (0.02)	0.06*** (0.02)
Private	-0.03 (0.03)	0.00 (0.02)	0.05* (0.02)	0.12** (0.05)	0.06 (0.03)
			Occupation *(Elementary Occupations)*		
Professionals and Managers	0.03 (0.02)	0.02 (0.01)	0.03** (0.01)	-0.01 (0.02)	0.09*** (0.02)
Skilled Workers and Service Providers	0.01 (0.03)	0.03 (0.02)	0.04* (0.01)	0.11*** (0.02)	0.03** (0.01)
Production and Craft Workers	0.13*** (0.03)	0.05* (0.03)	0.06** (0.02)	0.04 (0.02)	0.01 (0.01)
			Industry *(Public and Social Services)*		
Production and Extraction	-0.14*** (0.02)	-0.10*** (0.02)	-0.00 (0.01)	0.02 (0.03)	0.07*** (0.02)
Infrastructure and Utilities	-0.10*** (0.02)	-0.12*** (0.02)	-0.09*** (0.01)	0.00 (0.02)	0.04** (0.01)
Goods and Services	-0.11*** (0.02)	-0.11*** (0.01)	-0.04*** (0.01)	-0.05* (0.02)	0.00 (0.02)
Knowledge and Service-Based	-0.04*** (0.01)	-0.05*** (0.01)	-0.02** (0.01)	-0.13*** (0.02)	0.01 (0.02)

** for p<.05, ** for p<.01, *** for p<.001*
Standard errors are presented in parentheses, along with coefficient values.
Reference categories for independent variables are indicated in parentheses.

Workers with technical degrees showed more pronounced significance than those with diplomas or certificates. Occupational characteristics, such as being in regular/salaried employment, working in public enterprises, and holding professional or managerial positions, further contributed to the explained component of the wage disparity. The type of industry a person works in also significantly explains the gender wage gap for all industries, except for knowledge and services-based industries.

The unexplained component, indicative of potential discrimination and unobserved factors, showed that the age group of 30-44 years significantly impacted the unexplained gap. The OBC social group significantly affected the 50th and 75th percentile. Marital status influenced the unexplained component below the median, particularly for those divorced/separated. From having no formal education to postgraduate levels, educational attainment negatively affected the unexplained gap across most of the wage distribution, except at the 90th percentile, suggesting potentially diminished educational returns for females despite similar qualifications. Technical education had varied impacts across quantiles, with the unexplained component for degrees being mostly negative and significant at lower quantiles—indicating women received lower returns on similar qualifications compared to men—while at higher quantiles, the effect turned positive but not significant, suggesting a potential reversal in returns at the upper end of the wage distribution. Occupational factors, including regular/ salaried employment and working in public or private enterprises, significantly contributed to the unexplained component across the wage distribution. Additionally, the roles of skilled workers, service providers, and production and craft workers significantly impacted the unexplained gap, along with all the industry types having a significant effect on the unexplained portion of the gender wage gap, highlighting areas where discrimination or unobserved factors may be at play in perpetuating wage disparities.

Discussion

Our examination of the gender pay disparity within India's urban workforce, utilizing UQR and OB-RIF Decomposition, uncovered intricate details regarding the varied income levels between males and females.

The UQR modeling approach underscores the complex nature of wage determination, shaped by various factors such as demographic characteristics, socio-economic background, and job-related features. The study highlights wage disadvantages encountered by younger male employees, particularly those in the lowest age bracket, indicating that lack of experience and possibly weaker negotiation power in the job market may lead to reduced earnings for this group.

Furthermore, our findings point to the persistent influence of caste on wage differences, with SC and ST individuals, and particularly SC females in the top earning categories, facing substantial wage deficits. This underscores the complex interaction between gender and caste in shaping wage outcomes, consistent with Agrawal's (2013) and Mesvani's (2018) research. Our analysis aligns with the work of Arabsheibani et al. (2018), who demonstrated that the wage gap between the "Others" category and marginalized groups (SC, ST, OBC) had widened over time.

Specifically, they observed a 22 percent and 41 percent increase in the wage gap between Others-SC and Others-ST from 1993 to 2011, indicating an increased wage disparity influenced by caste. Marital status significantly influences wages, with a clear positive correlation for males across various wage levels, suggesting societal biases that favor married males as more stable and potentially impacting the labor market participation of married females. This trend was more evident among higher-earning females, suggesting unequal distribution of marriage benefits across genders. The study found that being widowed, divorced, or separated has a minimal effect on males' wages. Still, these marital statuses were linked to higher wages for females in lower-wage percentiles. This could indicate a selection into these statuses or reflect these groups' labor market challenges. Li et al. (2022) somewhat echoed these trends, showing that married men in Canada earned more than their unmarried peers, with widowed and single men having wage reductions of 6.2 percent and 3.8 percent, respectively. For women, the situation was reversed; unmarried women (single, divorced, separated) generally earned more than their married counterparts, with single and divorced women having 3.3 percent and 3.2 percent more earnings, respectively, which suggested a wage advantage for unmarried women at higher wage levels. Our research underscores the profound impact of education on enhancing wage prospects, particularly for female workers. The results highlighted the substantial benefits of higher education, especially at elevated income brackets, and pointed to the potential economic advantages for individuals lacking formal education. Technical education also showed increased wages for both genders in urban India, with females benefiting more consistently across various education levels and wage distributions than males. These findings align with the human capital theory, which posits that education enhances productivity and earnings. These findings are also supported by Mohanty (2021) and Nayak et al. (2021), who also recognized the economic uplift education provides. Agrawal (2012) also explored similar themes using the India Human Development Survey (IHDS) dataset from 2004-05. His analysis revealed that the returns on education escalated with the level of education attained. Specifically, the rates of return for primary, middle, secondary, higher secondary, and graduate levels were found to be 5.5 percent, 6.2 percent, 11.4 percent, 12.2 percent, and 15.9 percent respectively. These findings, derived through the Heckman estimation method for rural and urban areas, further substantiate the value of educational advancement in enhancing economic outcomes. The interplay between employment type, enterprise type, occupation, industries, and wages were complex, indicating that the employment sector and job nature were influential factors in determining wage levels, with public sector employment providing a wage premium.

The OB-RIF Decomposition analysis in this study revealed intricate characteristics of the gender wage disparity across various wage percentiles in the urban labor force. It uncovered a notable wage difference at lower wage tiers, where males outearned females, which diminished and flipped at upper wage tiers. This suggests varying gender impacts on wages throughout the wage spectrum (Agrawal, 2020; Chatterjee, 2023). The wage disparity at lower percentiles (10th, 25th, and 50th) highlighted females' challenges in lower-wage roles.

The explained component at these levels showed that factors like education and experience contributed to the wage gap. However, these did not fully explain the gender wage gap, pointing to significant discrimination as evidenced by a substantial unexplained component. Conversely, at higher percentiles (75th and 90th), the explained component became negative, suggesting that characteristics associated with higher wages benefit females more, potentially reflecting the successful leveraging of their skills and qualifications. However, the persistent positive unexplained component indicated ongoing gender-based disparities, even at higher wage levels (Pattaya et al., 2023). Agarwal (2013), using the NSSO 2009-10 dataset, also highlighted a consistent pattern of gender wage disparities across different wage percentiles, with a notable reduction in the wage gap from the lower to the higher percentiles. He showed that the gender log wage gap at the 10th percentile was over 0.7, and discrimination accounted for a wage difference where males earned 82 percent more than females purely due to discrimination. He also reported a gap of 0.30 log points at the median, corresponding to a 35 percent raw gender wage gap. Our study suggests that while the gap narrows, it remains significant and is primarily driven by discrimination. At higher percentiles, both studies observed a further narrowing of the gap. Agarwal (2013) noted a reduction in the wage gap due to discrimination to about 10 percent at the ninth decile. This suggested that at higher wage levels, the impact of discrimination diminishes significantly, though it does not disappear entirely. Our study shows that a narrowing and eventual reversal of the gap at higher wage levels offers a glimmer of hope but also underscores the need for continued efforts to address gender-based wage disparities across the entire wage spectrum.

The decomposition results also highlighted the intricate dynamics influencing the gender wage disparity in urban India. Factors including age, marital status, educational attainment, type of worker, occupation, and industry type accounted for some of the disparity, yet a significant portion remained unaccounted for. This suggests the existence of possible discrimination and unequal benefits from aspects such as education and job type. The enduring nature of this unexplained difference emphasizes the challenge of achieving wage equality between genders. It points to the necessity for precise policy measures to overcome visible and invisible obstacles to fair compensation. Future studies should continue to examine these issues, focusing on the changing conditions of the urban job market and how policy adjustments affect wage gaps.

Conclusion

Our research carefully utilized UQR and OB-RIF Decomposition to investigate the gender pay disparity in India's urban workforce. Through UQR, intricate relationships between various covariates and wage distribution for both genders were revealed, highlighting complex patterns of association. The analysis identified significant negative correlations between age and wages, a persistent adverse effect of caste affiliations on male wages, and the pronounced influence of marital status and education on wage levels across different quantiles. Moreover, the research outlined substantial wage penalties and premiums associated with employment type, enterprise type, and occupational categories, elucidating the multifaceted determinants of wage distributions. The OB-RIF decomposition method thoroughly analyzed the gender wage disparity among workers in urban India. It revealed a considerable salary gap that benefits males at the lower wage spectrum, attributing this difference to known and unknown factors. Moving towards the higher wage brackets, the gap appeared to narrow, indicating that females might display more highly regarded traits at elevated income levels than males or that discrimination might play a lesser role. Furthermore, the decomposition analysis showed that age, marital status, educational attainment, occupation, and industry types significantly contribute to the explained part of the wage gap. Conversely, educational attainments, occupation, and industry categories significantly influence the unexplained portion, particularly at the lower end of the wage scale.

The methods employed in the study, specifically UQR modeling and OB decomposition using RIFs, represent a significant advancement in methodology relative to traditional analysis techniques. These techniques allow for the breakdown of distributional statistics beyond the average, providing a more adaptable framework for analyzing wage formation, and they facilitate precise calculations of how each factor contributes to the composition and structure of wage impacts. RIF regressions have led to a more nuanced comprehension of the elements influencing wage inequality and gender differences throughout the wage distribution. This research's methodological precision and insights are vital for directing subsequent studies and shaping policies to foster a fairer and more just labor market.

This research highlights the intricate factors determining wages in India's urban areas, drawing attention to gender imbalances and the complex interaction of variables that affect wage distribution. To effectively bridge the gender pay gap in India's urban sector, holistic strategies are needed to dismantle wage inequities. Although laws like the Equal Remuneration Act and the Maternity Benefit Act promote gender equality, their success depends on strong enforcement and increased public awareness (Acts/Schemes Enacted and Being Implemented for Supporting Women in Changing Dynamics of Economy, n.d.). Strengthening these mechanisms is crucial for ensuring fair compensation for women in the workforce. Promoting female participation in high-paying STEM fields is vital, as these sectors offer lucrative opportunities. Supporting women entrepreneurs and providing gender-sensitive training can empower women to excel in diverse industries, including those traditionally dominated by men. Additionally, encouraging flexible work hours and remote work options can help balance professional and familial responsibilities, enhancing women's workforce participation. Collaboration between government bodies, industry associations, and educational institutions is essential to fostering an inclusive economy where women can thrive, which is imperative for achieving genuine gender parity in wages within India's urban labor market.

Conflict of Interest

No possible conflict of interest was reported by the author(s).

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References

Acts/schemes enacted and implemented to support women in changing dynamics of economy. (n.d.). https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1987736

Adireksombat, K., Fang, Z., & Sakellariou, C. (2016). The evolution of Gender Wage Differentials in Thailand: 1991–2007 — an application of unconditional quantile regression. *The Singapore Economic Review*, *61*(05), 1550094. https://doi.org/10.1142/s0217590815500940

Agrawal, T. (2012). Returns to education in India: some recent evidence. *Social Science Research Network*. https://doi.org/10.2139/ssrn.1989460

Agrawal, T. (2013). Gender and caste-based wage discrimination in India: some recent evidence. *Journal for Labour Market Research*, *47*(4), 329–340. https://doi.org/10.1007/s12651-013-0152-z

Agrawal, T. (2020). Gender segregation and wage differentials in India: the role of educational attainment and occupational choices. *International Journal of Manpower*, *42*(1), 1–20. https://doi.org/10.1108/ijm-10-2019-0466

Albrecht, J., Björklund, A., & Vroman, S. (2003). Is there a glass ceiling in Sweden? *Journal of Labor Economics*, *21*(1), 145–177. https://doi.org/10.1086/344126

Arabsheibani, G. R., Gupta, P., Mishra, T., & Parhi, M. (2018). Wage differential between caste groups: Are younger and older cohorts different? *Economic Modelling*, *74*, 10–23. https://doi.org/10.1016/j.econmod.2018.04.019

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *The Journal of Human Resources*, *8*(4), 436. https://doi.org/10.2307/144855

Chatterjee, N. (2023). Gender Wage Gap in Indian labour Market and Role of Government Policies: A Theoretical Perspective with an Empirical Overhaul. *Economic Affairs*, *68*(3). https://doi.org/10.46852/0424-2513.3.2023.37

Das, P. (2018). Wage gap and employment status in Indian labour Market: Quantile based Counterfactual analysis. *World Journal of Applied Economics*, *4*(2), 117–134. https://doi.org/10.22440/wjae.4.2.4

Deshpande, A., Goel, D., & Khanna, S. (2018). Bad karma or discrimination? Male–Female wage gaps among salaried workers in India. *World Development*, *102*, 331–344. https://doi.org/10.1016/j.worlddev.2017.07.012

Directorate General of Employment, Ministry of Labour and Employment, Government of India. (2023). *Female Labour Utilization in India*. https://dge.gov.in/dge/sites/default/files/2023-05/Female_Labour_Utilization_in_India_April_2023_final__1_-pages-1-2-merged__1_.pdf

Firpo, S., Fortin, N. M., & Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica*, *77*(3), 953–973. https://doi.org/https://doi.org/10.3982/ECTA6822

Firpo, S., Fortin, N., & Lemieux, T. (2018). Decomposing wage distributions using recentered influence function regressions. *Econometrics*, *6*(2), 28. https://doi.org/10.3390/econometrics6020028

Ganguli, I. and K. Terrell (2005). Wage ceilings and floors: The gender gap in Ukraine's transition. *IZA Discussion Paper*, *1776*.

Khanna, S., Goel, D., & Morissette, R. (2016). Decomposition analysis of earnings inequality in Rural India: 2004–2012. *IZA Journal of Labor & Development*, *5*(1). https://doi.org/10.1186/s40175-016-0064-8

Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica*, *46*(1), 33. https://doi.org/10.2307/1913643

Lama, S., Majumder, R., & University of Burdwan. (2018). Gender inequality in wage and employment in Indian labour market. *Journal of Academic Research in Economics, 482.* https://mpra.ub.uni-muenchen.de/93319/1/lama.pdf

Li, J., Dostie, B., & Simard-Duplain, G. (2022). Firm pay policies and the gender earnings gap: the mediating role of marital and family status. *Industrial & Labor Relations Review*, *76*(1), 160–188. https://doi.org/10.1177/00197939221093562

Machado, J. A., & Mata, J. (2005). Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics*, *20*(4), 445–465. https://doi.org/10.1002/jae.788

Mesvani, K. (2018). Caste Discrimination in the Indian Labor Market: Examining the Regional

Differences in the Effect of Caste Affiliation on Wage Inequality in India's Labor Market. *Senior Independent Study Theses*, *Paper 7968*. https://openworks.wooster.edu/independentstudy/7968

Ministry of Labour & Employment, Directorate General of Employment, Government of India. (2015). *National Classification of Occupations – 2015 Volume I*. Retrieved January 12, 2024, from https://www.ncs.gov.in/Documents/Nationalpercent20Classificationpercent20ofpercent20Occupationspercent20_Volpercent20I-percent202015.pdf

Mohanty, S. (2021). A distributional analysis of the gender wage gap among technical degree and diploma holders in urban India. *International Journal of Educational Development*, *80*, 102322. https://doi.org/10.1016/j.ijedudev.2020.102322

Nayak, P. P., Khatei, L., Hanhaga, M., Swain, K., & Mallick, R. K. (2021). Gender and Rural-Urban Literacy Disparity in India with Special Reference to Odisha. *International Journal of Creative Research Thoughts*, *9*(3), 2756–2765. https://ijcrt.org/papers/IJCRT2103338.pdf

Oaxaca, R. (1973). Male-female wage differentials in urban labour markets. *International Economic Review*, *14*(3), 693-709. https://doi.org/10.2307/2525981

Padhi, B., Mishra, U. S., & Pattanayak, U. (2019). Gender-based wage discrimination in Indian Urban Labour Market: An Assessment. *The Indian Journal of Labour Economics*, *62*(3), 361–388. https://doi.org/10.1007/s41027-019-00175-8

Pattayat, S. S., Parida, J. K., & Paltasingh, K. R. (2023). Gender Wage Gap among Rural Non-farm Sector Employees in India: Evidence from Nationally Representative Survey. *Review of Development and Change (Print)*, *28*(1), 22–44. https://doi.org/10.1177/09722661231172867

Rios-Avila, F. (2020). Recentered influence functions (rifs) in stata: Rif regression and rif decomposition. *The Stata Journal: Promoting Communications on Statistics and Stata*, *20*(1), 51–94. https://doi.org/10.1177/1536867x20909690

Sengupta, P., & Puri, R. (2021). Gender pay gap in India: A reality and the way forward—an empirical approach using quantile regression technique. *Studies in Microeconomics*, *10*(1), 50–81. https://doi.org/10.1177/2321022221995674

StataCorp (2013). *Stata Statistical Software: Release 13.1*. College Station, TX: StataCorp LLC.

Unit Level data of Periodic Labour Force Survey (PLFS) July 2022-June 2023 | Ministry of Statistics and Program Implementation | Government of India. (n.d.). https://microdata.gov.in/nada43/index.php/catalog/179

Waldmann, E. (2018). Quantile regression: A short story on how and why. *Statistical Modelling*, *18*(3-4), 203–218.

Walter, D., & Ferguson, S. (2022). The gender pay gap, hard truths and actions needed. *UN Women Asia and the Pacific*. https://asiapacific.unwomen.org/en/stories/op-ed/2022/09/the-gender-pay-gap-hard-truths-and-actions-needed