Wage Disparities Across Caste Groups in Nepal's Labor Market

Hemanta Panthi[1]

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[1] Adjunct Faculty
DAV College, Tribhuvan University
heymantpanthi@gmail.com

Abstract

Purpose – This study examines wage disparities across caste groups in Nepal's labor market, focusing on whether these differences arise from human capital endowments or structural discrimination.

Design/methodology/approach – Using data from the National Labor Force Survey (NLFS) 2017/18, this paper employs the Oaxaca-Blinder decomposition method to separate wage differentials into explained and unexplained components, identifying the role of education, experience, and other market-related factors.

Findings and Conclusion – The results indicate that caste-based wage gaps are largely driven by differences in education, experience, and other human capital factors rather than direct wage discrimination. However, lower returns to education for marginalized caste groups suggest the presence of structural barriers that persist in Nepal's labor market.

Implications – This study underscores the need for inclusive labor policies and targeted skill development programs to reduce caste-based economic disparities.

Originality/value – By applying the Oaxaca-Blinder decomposition to caste-based wage differentials, this paper provides new insights into the structural challenges affecting Nepal's labor market and contributes to policy discussions on labor inclusion.

Keywords – Caste groups, Nepal labor market, Oaxaca-Blinder decomposition, Wage discrimination

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1. Introduction

Nepal is an ethnically and culturally diverse country with deep-rooted social hierarchies shaped by the Hindu caste system. Historically, caste has dictated social and economic mobility, resulting in systematic exclusion and marginalization of lower caste groups. Despite constitutional protections and affirmative action policies, caste-based inequalities persist in the labor market, influencing access to education, employment opportunities, and wages. According to the 2021 Population Census, Nepal comprises 142 caste and ethnic groups. The largest groups include Chhetri (16.9%), Brahman-Hill (12.8%), Magar (7.1%), Tharu (6.6%), Tamang (5.6%), Newar (4.8%), Kami (4.8%), Muslim (4.4%), Yadav (4.0%), and Rai (2.3%). These statistics highlight Nepal's rich cultural diversity and the complex social fabric shaped by its caste and ethnic composition. Despite these demographic shifts, discriminatory practices, occupational segregation, and unequal access to quality education continue to contribute to wage disparities across caste lines. While caste-based discrimination is often compared to racial discrimination in the Western context, scholars argue that caste is a more rigid and enduring form of social exclusion, with implications extending beyond economic outcomes Discriminatory practices, occupational segregation, and unequal access to quality education contribute to wage disparities across caste lines. While caste-based discrimination is often compared to racial discrimination in the Western context, scholars argue that caste is a more rigid and enduring form of social exclusion, with implications extending beyond economic outcomes.

Economic theories suggest that wage differentials arise from both supply- and demand-side factors. On the supply side, lower caste individuals often possess fewer marketable skills due to historically restricted access to education and training. On the demand side, employers may engage in statistical discrimination, perceiving lower caste workers as less productive, thereby offering them lower wages. Moreover, informal labor networks often exclude marginalized groups, reinforcing economic disparities.

2. Review of Literature

Previous studies, such as Mainali (2017) and Karki and Bohara (2014), highlight that Dalits and other marginalized groups earn significantly lower wages than Brahman/Chhetris do, even after controlling for education and experience. The United Nations Development Program (UNDP) (2008) further reports that Dalits, despite legal protections, continue to face exclusion in education, employment, and social participation. The effectiveness of Nepal's affirmative action policies, including quotas in public institutions, remains a topic of debate, with limited empirical evidence on their impact on labor market outcomes. This study contributes to the existing literature by employing the Oaxaca-Blinder decomposition to quantify caste-based wage differentials, distinguishing between differences in human capital endowments and structural wage discrimination. By analyzing data from the Nepal Labor Force Survey (NLFS) 2017/18, we provide a rigorous assessment of the drivers of wage inequality and offer policy recommendations aimed at fostering greater labor market inclusivity.

The economic study of labor market discrimination is rooted in the seminal work of Becker (1957), who introduced the concept of taste-based discrimination, arguing that employers may exhibit a preference for certain groups, leading to wage differentials. However, competitive market forces should, in theory, erode such discriminatory practices over time. Extending this framework, Oaxaca (1973) and Blinder (1973) developed a decomposition technique to quantify wage disparities by separating differences in human capital endowments from unexplained factors often attributed to discrimination.

Oaxaca (1973) examined gender-based wage discrimination in the United States and found that a significant portion of wage disparities remained unexplained by observable characteristics. Similarly, Reimers (1983) explored wage gaps among Hispanic and Black workers, identifying education and language proficiency as critical factors influencing wage differentials. Banerjee (1985) applied this framework to caste-based wage discrimination in India, highlighting persistent disparities even after controlling for education and occupation.

Building on this literature, Madheswaran and Attewell (2007) employed decomposition methods to analyze caste discrimination in India's labor market, finding that a substantial portion of wage gaps remained unexplained, suggesting structural barriers beyond human capital differences. Studies by Chaudhary et al, (2024), Das (2007) and Madheswaran (2016), further refined these models by incorporating selection bias corrections and examining wage disparities across different employment sectors.

In the context of Nepal, Karki (2014) and Mainali (2017) have applied decomposition techniques to assess caste-based wage differentials. Karki (2014) found that the majority of earnings gaps between Dalits and non-Dalits were attributable to endowment effects, while Mainali (2017) highlighted occupational segregation as a key driver of wage disparities. These findings align with broader international literature, reinforcing the notion that marginalized groups face structural disadvantages in accessing higher-paying jobs and receiving equitable returns on education.

Despite policy interventions aimed at promoting social inclusion, caste-based wage disparities persist in Nepal's labor market. Affirmative action policies, such as reservation quotas in public institutions, have shown some success in reducing wage gaps, but their impact in the private sector remains limited. The existing literature underscores the need for targeted labor market policies that not only enhance educational access for marginalized groups but also address structural barriers that hinder their economic mobility.

This study builds upon previous research by employing the Oaxaca-Blinder decomposition to assess caste-based wage gaps in Nepal, incorporating additional controls for occupational and sectoral differences. By bridging gaps in existing empirical research, this paper aims to provide a comprehensive understanding of the mechanisms driving caste-based wage disparities and offer policy recommendations for fostering a more inclusive labor market.

3. Methods

Mincerian Wage Equation

The complexities of the caste system in Nepal are intertwined with religion and culture, and there is no fine distinction between the caste groups. We follow Muluki classification of caste groups and cluster into three broad categories as the higher caste group (Tagadhari caste), the middle caste group (Matwali caste), and the lower caste group (Paninachalne caste group). We use Mincerian wage equation (Mincer, 1974) to estimate the impact of education, experience, and other attributes on individual wages. The regression model is specified as:

$$logw = \beta_0 + \beta_1\, Educ + \beta_2\, Exp + \beta_3\, Exp^2 + \varepsilon$$

This framework assumes that wages reflect the price of productive attributes such as education and experience. Where logw represents the logarithm of an individual's wage, Educ denotes years of schooling, Exp represents work experience, approximated by an individual's age, Exp^2 accounts for the diminishing returns to experience. The model assumes that education has a multiplicative effect on earnings and that individuals maximize lifetime income by optimizing investment in education. The squared term for experience is included to capture the effects of on-the-job training and the declining returns to education over time, as suggested by the life-cycle human capital model (Mincer, 1974).

Oaxaca-Blinder Decomposition

The Blinder-Oaxaca methodology is a statistical technique used to analyze differences in group means, particularly in the context of labor market outcomes such as wages. The approach involves decomposing the wage gap between two groups, such as men and women or White and Black workers, into two components: one attributable to differences in group characteristics, such as education or experience, and another due to differences in the way these characteristics are rewarded in the labor market, which may indicate discrimination. This method can provide insight into the sources of wage differentials and help identify potential policy intervention areas (Blinder, 1973). The wage setting model is assumed to be linear and distinguishable in observable and un-observable characteristics as:

$$yl = X\beta g + \varepsilon g$$

where for g represents the caste categories, x is a vector containing the predictors and constant, β contains the slope parameters and intercepts, and ε is the error term. We take two groups from caste categories and outcome variable y and set of predictors. Letting Dk =1 be an indicator of higher caste group membership and taking the expectations over X, the overall mean wage gap Δμ0 can be written as:

$$\Delta\mu 0 = E[yk|Dk,= 1] - E[yk|Da = 0]$$

$$= E[E(yk|X,Dk = 1)|Dk = 1] - E[E(ya|X,Dk = 0)|Dt = 0]$$

$$= (E[X|Dk = 1]\beta t + E[\varepsilon t|Dk = 1]) - (E[X|Dk = 0]\beta a + E[\varepsilon a|Da = 0])$$

Where, $E[\varepsilon a|Da = 0] = E[\varepsilon t|Dt = 1] = 0$). Adding and subtracting the average counterfactual wage that Higher caste group workers would have earned under the group structure of A/J, $E[X|Dk = 1]\beta a$, the expression becomes:

$$\Delta\mu 0 = E[X|Dk = 1]\beta t - E[X|Dk = 1]\beta a + E[X|Dk = 1]\beta a$$

$$+ E[X|Dk = 1]\beta a - E[X|Dk = 0]\beta a$$

$$= E[x|Dk = 1](\beta k - \beta a) + (E[X|Dk = 1] - E[X|Da = 0])\beta a$$

Replacing the expected value of the covariates $E[x|Dt = d]$, for d = 0, 1, by the sample averages $\bar{X}g$, the decomposition is estimated as:

$$\Delta\mu 0 = \bar{X}k\hat{\beta}k - \bar{X}k\hat{\beta}a + \bar{X}k\hat{\beta}a - \bar{X}a\hat{\beta}a$$

$$= E[X|Dk = 1](\beta k - \beta a) + (E[X|Dk = 1] - E[X|Dk = 0]\beta a$$

Replacing the expected value of the covariates $E[X|Dk = d]$, for d= 0,1 by the sample averages $\bar{X}g$, the decomposition is estimated as

$$\Delta\mu 0 = \bar{X}k\hat{\beta}k - \bar{X}k\hat{\beta}a + \bar{X}k\hat{\beta}a - \bar{X}a\hat{\beta}a$$

$$= \bar{X}k(\hat{\beta}k - \hat{\beta}a) + (\bar{X}k - \bar{X}a)\hat{\beta}a$$

The first term in the above equation $\bar{X}k(\hat{\beta}k - \hat{\beta}a)$ is the wage structure effect, also called the "Unexplained " part of wage differentials, or the "Discrimination" whereas the second term in above equation $(\bar{X}k - \bar{X}a)\hat{\beta}a$ is the composition effect or explained component. If Da = 1 be an indicator of middle caste membership and taking the expectations over X, the overall mean wage gap would be $\Delta\mu 0 = \bar{X}a(\hat{\beta}a - \hat{\beta}k) + (\bar{X}a - \bar{X}k)\hat{\beta}k$. For the two-fold decomposition an unknown nondiscriminatory coefficient vector β* is needed. There may be a reason to assume that discrimination is directed towards a specific group so that β* = βkorβ* = βa. But there are no specific reasons to assume that coefficient of one or other group are non-discriminating. Taking a group beta coefficient as reference can undervalue the comparison group and overvalue the reference group. To overcome the problem Reimers (1983) proposed to use the average coefficient over both groups as an estimated for the nondiscriminatory parameter vector, i.e. β^* = 0.5(β^k) + 0.5(β^a) as pooled model. We follow the Reimers proposition for our decomposition analysis.

Heckman Two-Step Correction for Selection Bias

Since wages are only observed for individuals participating in the labor force, the analysis is prone to selection bias. To address this, we apply Heckman's (1979) two-step selection correction method. The inverse Mills ratio (IMR) is first estimated using a probit model of labor force participation: P(LF_i=1)=ϕ(Z_i γ) Where Z_i represents the determinants of labor force participation. The IMR is then included as an additional regressor in the wage equation:

$$logw= \beta_0+\beta_1 Educ+\beta_2\ Exp+\beta_3\ Exp^2+\lambda IMR+\ \varepsilon$$

Data Source and Sampling Strategy

This study utilizes the third wave of the Nepal Labor Force Survey (NLFS) 2017/18 conducted by the Central Bureau of Statistics (CBS). The survey employs a two-stage stratified sampling technique, covering 18,000 households from 900 primary sampling units (PSUs) across Nepal. The sampling framework follows the 2011 National Population and Housing Census, with stratification based on urban and rural regions within Nepal's seven provinces. To ensure representativeness, the sampling units were stratified into three levels using the Lavallee-Hidiroglou (LH) algorithm, which minimizes variance across strata. The final sample was drawn using probability proportional to size (PPS), with 20 households systematically selected per PSU.

4. Results

The descriptive analysis reveals persistent caste-based disparities in education, employment, wages, and gender participation. Lower castes have the lowest educational attainment, particularly in higher education, while Higher caste individuals have the highest privileges. Despite similar education levels, higher caste workers earn more than middle and lower caste individuals do, highlighting wage gaps beyond human capital differences.

Employment patterns show Higher caste dominance in government jobs, while Middle and Lower castes are more concentrated in private businesses and informal sectors, earning lower wages across all sectors. Women's workforce participation remains low, with a significant gender wage gap across all caste groups. Urban workers earn more than rural workers, with high caste individuals having greater urban representation. Middle and Lower groups are overrepresented in low-paying elementary and agricultural jobs, while High caste individuals are more likely to hold managerial and professional roles.

Oaxaca-Blinder: Human capital model

Using Oaxaca-Blinder decomposition, we analyze caste-based wage differentials through three models: High vs. Middle, High vs. Lower, and Middle vs. Lower caste group, with 6673, 4536, and 5651 observations, respectively. The human capital model isolates the role of education and experience in wage disparities, aligning with the theory that earnings are a function of an individual's human capital endowments.

Caste-wise decomposition reveals that unadjusted hourly wages are highest for Higher caste (Rs. 92.33), followed by Middle (Rs. 72.73) and Lower (Rs. 61.32). Wage differentials are 26% (high vs middle), 50% (high vs lower), and 18% (middle vs lower). After adjusting for Inverse Mills Ratio (IMR), wages rise across all groups, and the wage gap slightly narrows. The composition effect (explained component) accounts for 19% of the high vs middle gap, 28% of the high vs lower gap, and 7% of the middle vs lower gap, while the structural effect (unexplained component) remains insignificant in all cases.

Sectoral decomposition further shows that government employees earn significantly higher wages than those in the private and informal sectors. Unadjusted hourly wages are highest in the government sector (Rs. 118.40) followed by private institutions (Rs. 73.12), private businesses (Rs. 67.52), and other sectors (Rs. 66.78). Wage gaps between the government and other sectors range from 61% to 77%. After adjusting for IMR, wages increase across all sectors, and wage differentials shrink. The adjusted wage gap between government and private businesses (32%), private institutions (39%), and other institutions (34%) is primarily driven by composition effects (40%, 21%, and 51%, respectively). As with caste decomposition, the structural effect remains insignificant, suggesting that wage disparities are largely attributable to differences in education, experience, and other observable factors rather than direct discrimination.

Oaxaca-Blinder: Full Specification

Building upon the previous model, this specification incorporates additional socio-economic controls, including migration status, marital status, vocational training, job classification, overtime status, urban residency, and Muluki group/employment sector, to provide a more comprehensive analysis of wage differentials.

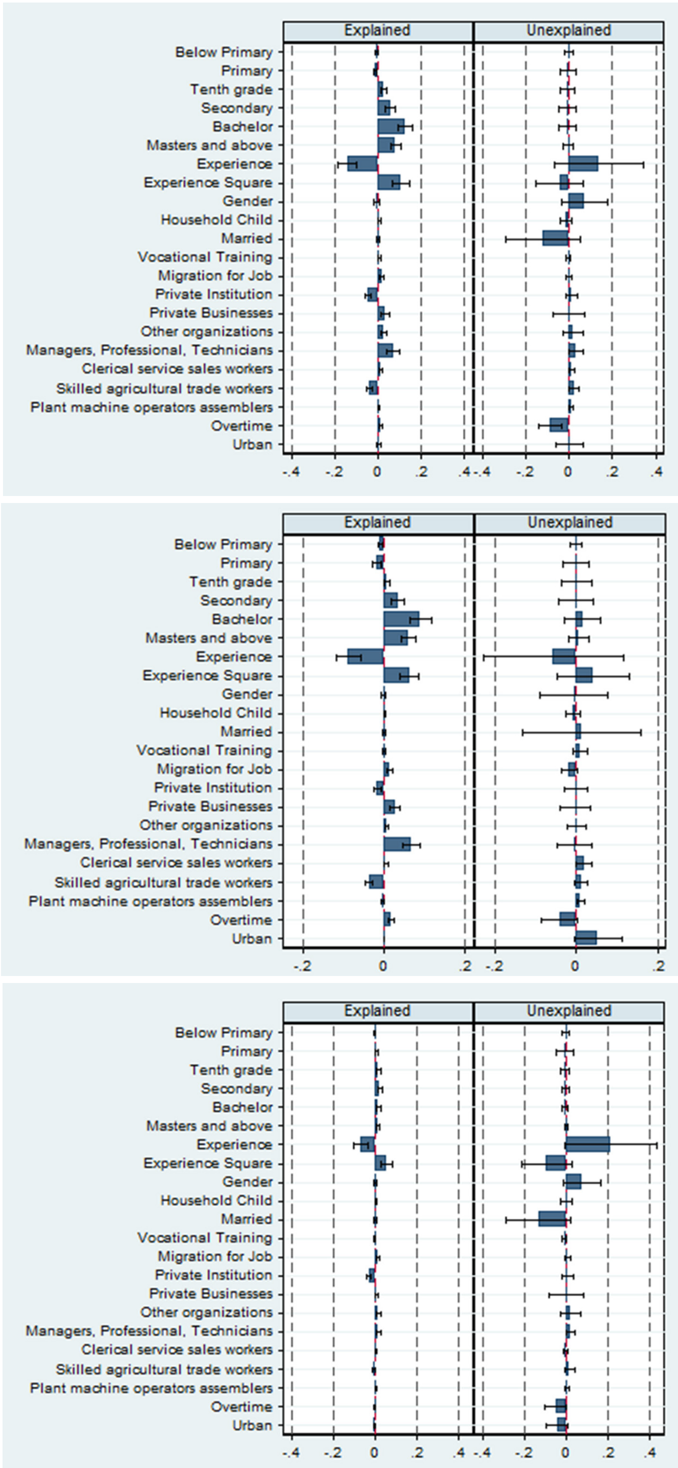
Table 3 (annex) presents the results of caste-based wage decomposition. The mean wages for the higher, middle, and lower caste groups are Rs. 92.33, Rs. 72.73, and Rs. 61.32, respectively. The observed wage gaps are 26% (high vs middle), 50% (high vs lower), and 18% (middle vs lower). After adjusting for Inverse Mills Ratio (IMR), the estimated wages increase for high and middle groups while decreasing for lower caste, with adjusted wages of Rs. 117.75 (higher), Rs. 97.53 (middle), and Rs. 52.85 (lower). The adjusted wage differentials are 20% (high vs middle), 122% (high vs low), and 84% (middle vs low), indicating that the initial estimates underestimated the wage gaps in models comparing Dalit workers.

Decomposing wage differentials into explained (composition effect) and unexplained (structural effect) components, 22% of the high vs middle wage gap is attributed to composition effects, suggesting that if middle caste workers had the same endowments as high caste workers, their wages would increase by 22%. The remaining negative 2% unexplained component is statistically insignificant. 36% of the high vs lower caste wage gap is explained, while 63% remains unexplained, implying that equalizing lower workers' human capital endowments to those of high caste workers would increase their wages by 36%. 8% of the middle vs lower caste wage gap is explained, with 69% unexplained, indicating that adjusting lower caste workers' endowments to match middle caste levels would increase their wages by 8%.

The explained components across all models are statistically significant at the 1% level, confirming that differences in human capital are the primary drivers of wage disparities. The unexplained component remains statistically insignificant, suggesting that structural discrimination does not play a major role in wage differentials across caste groups. A graphical representation of the decomposition results is provided in Figure 1 below.

Figure 1

Oaxaca-Blinder decomposition between different caste groups (1st panel – High vs Middle, 2nd panel- High vs Lower, 3rd panel – Middle vs Lower caste group)



5. Discussion and Conclusion

Caste-based discrimination remains a deeply entrenched socio-economic issue in Nepal, shaped by a rigid hierarchy that has persisted for centuries. Unlike racial discrimination, which emerged through historical processes such as colonization and slavery, caste-based exclusion is institutionalized through cultural and occupational structures. Nepal's caste system, rooted in patriarchal values, continues to marginalize lower-caste groups, particularly Dalits, limiting their access to education, employment opportunities, and political representation. While legislative reforms, such as the Bill on Caste-Based Discrimination, have been enacted to criminalize caste-based exclusion and promote social inclusion, the persistence of economic disparities highlights structural barriers that remain unaddressed.

The findings from the Mincerian wage equation confirm that education plays a crucial role in determining earnings across caste groups. High caste individuals benefit from better educational attainment and greater institutional earnings, translating into higher hourly wages (Rs. 117.5 for High, Rs. 97.53 for middle, and Rs. 52.85 for Lower castes). Despite the government's affirmative action policies, the analysis reveals that lower caste groups remain disproportionately concentrated in low-skilled jobs, with limited access to high-paying occupations. This aligns with Akerlof (1976) and Karki and Bohara (2014), who attribute wage disparities largely to endowment effects rather than outright wage discrimination.

The Oaxaca-Blinder decomposition further demonstrates that composition effects, such as differences in education and experience, account for the majority of wage disparities, while unexplained wage structure effects remain statistically insignificant. For instance, if Lower caste workers had the same human capital endowments as Higher caste workers, their wages would increase by 36%, underscoring the role of educational and occupational disadvantages in perpetuating economic inequality. While government policies have facilitated some degree of inclusion, marginalized groups continue to face systemic barriers in accessing quality education and skilled employment, reinforcing intergenerational cycles of poverty and exclusion.

To address these disparities, policy interventions must go beyond legal protections and focus on enhancing access to quality education, vocational training, and employment opportunities. Strengthening early education programs, providing targeted skill development initiatives, and ensuring equal access to high-paying occupations are crucial in breaking the cycle of caste-based economic exclusion. Although Nepal has made strides in promoting caste-based inclusion in governance, a more comprehensive approach is needed to bridge the persistent wage gaps and create a truly equitable labor market.

6. Limitations and Future Direction

This analysis focuses on average wage differentials, which may mask important variations across the wage distribution. Wage disparities often differ significantly at various points of the income spectrum. Future research could apply Chernozhukov's counterfactual decomposition (Chen, 2016) to explore these differences across quantiles in more detail. Additionally, caste may influence psychological and behavioral factors that shape an individual's performance and opportunities in the labor market. These dimensions are complex and warrant deeper investigation in future studies.

Conflict of Interest

The author declares that there is no conflict of interest.

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Appendix

Table 1: Probit estimates for Labor Market Participation.

Employed	Coef.	Std. Err.	z	P\ textgreater{}|z|	95\% Conf. Interval
Schooling years	.0447031	.0014746	30.31	0.000	.0418129 .0475933
Chores hour	-.3312476	.0261533	-12.67	0.000	-.3825072 -.279988
Urban	.1611043	.0154562	10.42	0.000	.1308107 .1913978
Household child	.0106473	.0056514	1.88	0.060	-.0004291 .0217238
Marital status	.5348234	.0175618	30.45	0.000	.5004028 .5692439
Muluki Group					
Matwali	.2648757	.0167611	15.80	0.000	.2320244 .2977269
Pani nachalne	.3788027	.0213821	17.72	0.000	.3368947 .4207108
Gender	-.8966224	.0150293	-59.66	0.000	-.9260794 -.8671655
Constant	-1.441151	.026401	-54.59	0.000	-1.492896 -1.389406

Table 2: Wage estimates for caste groups and pooled data.

	UP	Middle	Lower	Higher	Pooled
Schooling years	0.042***	0.043***	0.094***	0.097***	0.048***
Experience	0.023***	0.024***	0.015***	0.018***	0.022***
Experience Square	-0.0003	-0.0003***	-0.0002***	-0.0002***	-0.0003***
Mills	0	0.229	2.104***	1.326***	0.242***
Vocational Training	0.001	-0.026	0.056	0.011	-0.0002
Gender (Male)	-0.247***	-0.396*	-1.747***	-1.161***	-0.416***
Married	0.037***	0.126	0.921***	0.586***	0.137***
Child	-0.009**	-0.004	0.007	0.002	-0.006
Chores hour	-0.018	-0.1	-0.535***	-0.393***	-0.084***
Overtime	-0.084***	-0.080***	-0.008	-0.147***	-0.084***
Migrated	0.149***	0.173***	0.104***	0.115***	0.144***
Urban	0.012	0.009	0.265***	0.200***	0.040***
Firm type ^{1}					
Private Institutions	-0.226***	-0.221***	-0.260***	-0.206***	-0.222***
Private Business	-0.079	-0.098***	-0.093*	-0.080**	-0.071***

others Business	-0.102***	-0.092***	-0.170***	-0.060*	-0.095***
Job sector^2					
MPT ^{3}	0.306***	0.351***	0.151***	0.261***	0.302***
CSSW^4	0.058***	0.026	0.087**	0.086***	0.055***
SAT^5	0.207***	0.221***	0.171***	0.273***	0.22***
PMOA^6	0.209***	0.064**	0.057	0.182***	0.083***
Constant	3.748***	3.422***	0.572	1.194*	3.356***
Observations	8430	3894	1757	2779	8430
R2	0.409	0.348	0.275	0.459	0.411
Adjusted R2	0.408	0.345	0.267	0.455	0.41
Residual Std. Error	9.033	8.851	8.657	9.195	9.02
F Statistic	323.995***	109.002***	34.613***	123.017***	309.191***

***, **, * represent significance at 1\%, 5\% and 10\%

^{1} = Taking government institution as base group

^{2} = Taking elementary Occupations as base group

^{3}= Managers, Professionals, Technicians

^{4} = Clerical service sales workers

^{5}= Skilled agricultural trade workers

^{6}= Plant machine operators and assemblers

Source: Author computation

Table 3: Oaxaca Blinder decomposition of wage differentials

Group 1	Higher	Higher	Middle
Group 2	Middle	Lower	Lower
Overall			
Group 1	92.33***	92.33***	72.73***
Group 2	72.73	61.32	61.32
Difference	1.26***	1.50***	1.18***
Adjusted			
Group 1	117.75***	117.75***	97.53***
Group 2	97.53***	52.85***	52.85***
Difference	1.2	2.22*	1.84*
Composition	1.22***	1.36***	1.08***
Wage Structure	0.98	1.63	1.69
N	6673	4536	5651

***, **, * represent significance at 1\%, 5\% and 10\%

Source: Author computation