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Gender-based differences in employment opportunities and wage distribution in Nepal

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ABSTRACT

The gender wage gap has long been a critical aspect of gender inequality. The issue is even more crucial for countries such as Nepal, where there are significant differences between men and women in educational attainment levels. This study investigates how educational attainment affects occupational choice for men and women in urban and rural areas. The result shows that females in rural areas have difficulty finding regular work even when their educational attainment level is controlled, compared with males and urban females. In addition, our decomposition results show that regular female workers in rural areas face a large wage gap owing to gender discrimination effects. These results indicate that, despite high education levels on par with males or urban females, rural females have fewer opportunities to find regular work and face significant wage discrimination. This may explain the perceived low incentives in educating girls in rural Nepal. This study contributes to the literature on gender wage gap by expanding the analysis to regular and casual labor markets and to urban and rural areas.

1. Introduction

Women have long received relatively less pay compared to men in many developing countries (World Bank, 2012). The social view that women are less productive due to their lower levels of education leads to this inequality in pay. Although improvement in women's education level has positive impacts on quality of life, including higher earnings, larger returns to education (Schultz, 2002), national economic growth and development (Dollar & Gatti, 1999; Hassan & Cooray, 2015; Klasen, 2000; World Bank, 2001), and improvement in health and schooling of children (Schultz, 2002), women still receive less education than men do in many developing regions. In recent decades, the delay in improving women's education in developing regions has been emphasized in international discussions on gender empowerment. Various policies have addressed low enrolment rates in developing countries, and have found that the average years of schooling among those aged 15 years and over in developing countries has sharply increased from 2 years in 1950 to 7.2 years in 2010 (Barro & Lee, 2013).

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Many studies in economics address the gender wage gap to explain why women receive lower wages. Previous studies identified differences between men and women in experience and tenure (Blau & Kahn, 1997), educational attainment (Nakavachara, 2010), occupations (Alez-Aller, Longás-García, & Ullibarri-Arce, 2011; Groshen, 1991), working life cycles (Joshi, Makepeace, & Dolton, 2007), differences in the ratios of promotion for men and women (Booth, Francesconi, & Frank, 2003), and women having to look after children (Waldfogel, 1997) as drivers of gender wage inequality. Some studies pointed out that society views women as less valuable to educate (e.g., Hossain & Tisdell, 2005), which might cause lower education levels and wages among women compared to men.

Another explanation of the gender wage gap is the discrimination against women in the labor market. To identify wage discrimination in developing countries, the decomposition method has been applied (see Blinder, 1973; Oaxaca, 1973) to wage distributions, which decomposes wage gaps into factors explained by differences in individual characteristics and those not explained by their characteristics (Ahmed & Maitra, 2015; Ganguli & Terrell, 2005; Nopo, 2007; Pham & Reilly, 2007). This discrimination means that women with capabilities similar to men receive lower pay just because "they are women." This limits the impact of policies attempting to improve female education. From a policy perspective, it is important to understand the source of gender inequality. Discrimination inhibits girls from attending school because the perceived value of educating them becomes smaller than expected.

While the Nepalese economy has improved,[1] gender inequality is still widely prevalent in Nepal: the country ranks 118th out of 189 on gender equality (Sharma, Guha-Khasnobis, & Khanal, 2014). Gender inequality in Nepal is manifested in various aspects such as labor market participation (Acharya, 2014, chap. 2), household decision-making power (Kabeer, 1999), reproductive health care (Yamamoto & Matsumoto, 2017), child marriage (Choe, Thapa, & Mishra, 2005), and violence against women (Puri, Tamang, & Shah, 2011). From an economic point of view, the Gender Empowerment Measure (GEM) indicates the relative empowerment of women and men in various aspects including economic and political differences. The GEM in 2011 was 0.534 for the entire country, and 0.481 and 0.551 for the far western and central regions, respectively (Sharma et al., 2014). Regarding education, although the government implemented a free primary school system in the 1970s, the educational attainment level of rural girls remains low. The United Nations Children's Fund lists Nepal among the 25 priority countries for improving the school attendance ratio of girls (United Nations Children's Fund (UNICEF), 2003). As of 2010, the mean years of schooling in Nepal was 3.9 years for the entire country (4.6 years for males and 3.3 years for females), and 4.9 years and 3.6 years in urban and rural areas, respectively (Sharma et al., 2014). There is a serious need for improvement in women's education in Nepal.

In this study, we investigate the gender wage gap in occupation status (i.e., regular and casual work) and wage distributions, focusing on rural and urban areas in Nepal. As human capital accumulation (e.g., years of schooling) and industrial structure vary between rural and urban areas, the gender gap structure might differ in the two areas. Understanding the difference in the influence of gender inequality between rural and urban areas could help improve education among women in rural areas. Using data from the Nepal Living Standards Survey (NLSS), we employ multinomial logit models to estimate the impact of educational attainment on the choice of occupation status in urban and rural areas. Furthermore, we expand our analysis by employing the quantile technique to decompose the gap at different points of the wage distribution. We then perform decomposition at the selected quantiles using an Oaxaca–Blinder approach based on the recentered influence function (RIF) regression developed by Firpo, Fortin, and Lemieux (2009). For gender empowerment to be effective, it is necessary to understand the source of the gender wage gap.

This study contributes to the literature on gender wage gap by expanding the analysis to regular and casual labor markets and to urban and rural areas. While previous studies focus on the manufacturing sector (e.g., Ahmed & McGillivray, 2015; Koirala, 2007), many women are still engaged in the agricultural sector (or in the unskilled casual work sector), especially in the rural areas of developing countries.

The remainder of this paper is organized as follows. Section 2 presents the empirical framework to analyze gender differences in wage, in regular and casual work. Section 3 describes the data set and characteristics of workers in Nepal. Section 4 presents our estimation results and Section 5 concludes the paper.

2. Empirical framework

The gender wage gap can be defined as the difference in wages received by males and females, irrespective of their characteristics. We employ ordinary least squares (OLS) regression to estimate this male wage premium in each status of employment:

$$\ln w_i = \beta K_i + X_i \beta' + u_i, \tag{1}$$

where i denotes individuals, w_i denotes the monthly wages, K_i denotes the gender dummy, which takes the value of 1 if the worker is male and 0 if the worker is female, X_i denotes the vector of variables affecting market wages, and u_i is error term, which is independent of X_i. β and β' are the vectors of the coefficients to be estimated.

[1] After democratization in 1990, Nepal has witnessed substantial economic growth: the average annual GDP growth rate was 4.43% between 1995–2011 which increased to US$18.9 billion in 2011, and poverty rates declined by about 16.8% during the same period (World Bank., 2019; World Factbook., 2019).

To identify the causes of the gender wage gap, we employ an Oaxaca–Blinder decomposition at each quantile of the wage distributions. Define D as the difference in the expected value of wage obtained from Eq. (1) for males and females:

$$\begin{aligned} D(q) &= E[\ln W_m](q) - E[\ln W_f](q) \\ &= (E[X_m] - E[X_f])\beta_m(q) + X_f(\beta_m(q) - \beta_f(q)), \end{aligned} \tag{2}$$

where W_m and W_f is the males' and females' monthly wage. The first term of the right-hand side of Eq. (2) is the explained component of wage gap attributed to differences in observed characteristics. The second term is a component that cannot be explained by differences in characteristics and is interpreted as wage discrimination in the market. We present the gender wage gap at the qth quantile (q = 0.10, 0.25, 0.50, 0.75, and 0.90) on RIF regression estimates (see Fortin, Lemieux, & Firpo, 2011). They can show decomposition for any quantile of the wage distribution.[2]

Our analysis focused on both regular and casual employment status. However, individuals do not choose their employment statuses randomly. One way to correct possible selection bias is to employ the two-step technique from Heckman (1979). In the first stage, we estimate the inverse of Mill's ratio (λ) to determine the employment status for each individual. The probability of being a regular or casual employee and of being unemployed are, respectively:

$$P(y_i = j|Z_i) = \pi_{ij}, \tag{3}$$

$$\pi_{ij} = \frac{\exp(Z_i' \beta_j)}{\sum_{r=i}^{J} \exp(Z_i'\beta_j)}, \tag{4}$$

where j denotes the employment status (j = r: regular, c: casual, and n: unemployed), Z denotes the individual characteristics that are assumed to affect the probability of employment status but not affect wages, and π_{ij} is an indicator variable that takes the value of 1 if the individual i is employed in job type j.

Thus, a monthly wage equation from Eq. (1) could be converted as follows:

$$\ln w_i = \beta K_i + X_i\beta' + \sigma\lambda_i(X_i Z_i) + u_i, \tag{5}$$

where λ is from the first-stage regression of Eq. (4). We can control for sample selection bias by estimating (5). We can compute the gender wage gap with selection effects based on Eq. (3) as follows:

$$\begin{aligned} D(q) &= E[\ln W_m](q) - E[\ln W_f](q) \\ &= (E[X_m] - E[X_f])\beta_m(q) + X_f(\beta_m(q) - \beta_f(q)) + (\sigma_m E[\lambda_m] - \sigma_f E[\lambda_f]), \end{aligned} \tag{6}$$

where $(\sigma_m E[\lambda_m] - \sigma_f E[\lambda_f])$ denotes the contribution of differences in the average selection effect. There are several ways to treat the selection bias in decomposition analysis. In this study, we treated it as an additional effect to both the expected and discrimination effects.

3. Data

We employ the third wave of the NLSS which was the latest living standard survey for Nepal conducted in 2010–2011. The survey followed the Living Standards Measurement Survey methodology developed by the WorldBank (Central Bureau of Statistics (CBS), National Planning Commission, 2011). The sample employed in our analysis comprises working and non-working individuals in urban and rural areas. Based on how workers receive payment, they can be classified as having one of two types of employment status: regular and casual employment. Workers receiving payment on a monthly basis are considered regular workers and those receiving payment on a daily basis are considered casual.[3] We confine the sample to wage workers aged between 16 and 65 years.[4] Thus, the number of individuals in our data set is 4655 for urban and 9727 for rural regions.

The data on earnings and working status are available for all individuals. Table 1 provides the summary statistics for mean monthly earnings and the characteristics of working age by gender and employment status in urban and rural areas. Monthly earnings from regular employment include the base salary, bonuses, and additional payments from employers, while monthly earnings from casual employment are the average earnings in working months.[5]

[2] It should be noted that both mean and quantile decomposition are based on some assumptions (for a comprehensive survey, see Fortin et al., 2011). First, all decompositions in this paper depend on parametric assumptions on the conditional average and quantile functions. In many cases, including this paper, these functions are assumed to be linear functions. However, specification tests of the functional form are difficult to carry out. The second and more serious assumption is of interpretability. Even though decomposition results are often interpreted as causal mechanisms, Huber (2015) argues that such interpretations require sequential ignobility (no confounders between mediators and outcome variables). Despite these limitations, the decomposition method seems to have the potential to describe the reasons behind the difference between groups.

[3] We also define workers who receive payment on a contractual basis as regular workers.

[4] To focus on wage market analysis, students and individuals with missing information about their characteristics were excluded from the sample.

[5] In NLSS, employers of casual workers reported daily earnings in cash and payments in kind. We aggregated these values and multiplied daily payment by 30 to estimate the monthly wage.

Table 1
Summary statistics of the dependent and explanatory variables.

Urban

Variable	Male						Female					
	Regular		Casual		Unemployment		Regular		Casual		Unemployment	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
lwreg	9.101	0.903	–	–	–	–	8.487	1.112	–	–	–	–
lwcas	–	–	5.188	1.005	–	–	–	–	4.366	1.071	–	–
schoolyear	9.205	4.737	4.190	3.907	7.899	4.546	7.732	5.613	2.358	3.555	4.751	4.761
age	36.565	10.834	36.648	12.124	41.614	13.104	33.906	10.147	35.868	10.873	38.656	12.869
nepali	0.622	0.485	0.500	0.501	0.552	0.498	0.618	0.487	0.627	0.485	0.606	0.489
hhead	0.624	0.485	0.713	0.453	0.630	0.483	0.213	0.410	0.302	0.460	0.178	0.383
hsize	5.418	2.444	5.929	2.364	5.641	2.937	5.196	2.858	5.387	2.367	5.429	2.752
hcaste	0.621	0.485	0.329	0.471	0.618	0.486	0.672	0.470	0.283	0.452	0.591	0.492
mcaste	0.249	0.432	0.403	0.491	0.258	0.438	0.213	0.410	0.448	0.498	0.281	0.450
lcaste	0.131	0.337	0.268	0..443	0.124	0.329	0.114	0.318	0.269	0.444	0.128	0.335
firstjob	0.832	0.374	0.597	0.491	0.001	0.032	0.921	0.271	0.453	0.499	0.001	0.023
childltsix	0.504	0.787	0.574	0.824	0.502	0.733	0.504	0.824	0.462	0.691	0.536	0.769
childgtsix	0.889	1.008	1.297	1.234	0.976	1.241	0.829	0.989	1.396	1.202	1.044	1.196
illness	0.148	0.355	0.103	0.305	0.177	0.382	0.141	0.349	0.170	0.376	0.206	0.405
married	0.831	0.375	0.816	0.388	0.830	0.376	0.705	0.457	0.792	0.407	0.857	0.350
widow	0.008	0.090	0.016	0.126	0.022	0.147	0.057	0.232	0.094	0.293	0.073	0.260
divorced	0.004	0.059	0.023	0.149	0.008	0.089	0.032	0.177	0.033	0.179	0.013	0.112
hincome	9667.16	23,579.00	3524.79	7117.07	4314.54	11,409.67	16,410.39	38,128.50	3733.87	7961.76	7595.58	18,387.92
Observations	857		310		995		403		212		1878	

Rural

Variable	Male						Female					
	Regular		Casual		Unemployment		Regular		Casual		Unemployment	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
lwreg	8.467	1.214	–	–	–	–	7.485	1.605	–	–	–	–
lwcas	–	–	4.657	0.915	–	–	–	–	4.312	0.851	–	–
schoolyear	6.435	4.552	2.678	3.194	4.67	4.242	5.692	4.816	0.948	2.186	1.995	3.358
age	36.694	11.362	39.844	12.542	42.987	14.339	34.277	10.238	36.655	11.814	37.677	13.843
nepali	0.565	0.496	0.509	0.500	0.504	0.500	0.610	0.489	0.490	0.500	0.563	0.496
hhead	0.633	0.482	0.728	0.445	0.668	0.471	0.270	0.446	0.296	0.457	0.158	0.365
hsize	6.355	2.858	6.561	2.533	6.273	3.163	5.113	2.281	5.839	2.429	6.137	3.086
hcaste	0.403	0.491	0.240	0.427	0.360	0.480	0.484	0.501	0.204	0.403	0.376	0.484
mcaste	0.403	0.491	0.504	0.500	0.527	0.499	0.358	0.481	0.475	0.500	0.471	0.499
lcaste	0.171	0.377	0.257	0.437	0.113	0.316	0.157	0.365	0.321	0.467	0.153	0.360
firstjob	0.548	0.498	0.218	0.413	0.001	0.033	0.572	0.496	0.244	0.430	0.000	0.015
childltsix	0.813	1.019	0.855	1.045	0.837	1.076	0.384	0.593	0.717	0.906	0.947	1.121
childgtsix	1.438	1.359	1.594	1.311	1.414	1.486	1.214	1.187	1.679	1.277	1.409	1.393
illness	0.122	0.328	0.146	0.353	0.200	0.400	0.245	0.432	0.204	0.403	0.210	0.407
married	0.873	0.334	0.894	0.308	0.853	0.354	0.767	0.424	0.830	0.375	0.877	0.328
widow	0.009	0.096	0.027	0.162	0.031	0.174	0.044	0.206	0.077	0.266	0.065	0.246
divorced	0.004	0.063	0.012	0.108	0.009	0.094	0.025	0.157	0.019	0.136	0.010	0.102
hincome	3563.13	18,754.03	1658.17	15,100.41	1390.48	4574.07	4766.59	8454.56	2151.97	19,061.52	2356.61	9724.14
Observations	761		1706		1785		159		1121		4197	

The dependent variables in our estimation are the log monthly wage in regular and casual employment (*lwreg* and *lwcas*, respectively). The worker and household characteristics (explanatory variables) we used include years of schooling (*schoolyear*), age and age squared (*age* and *age2*, respectively), gender (*male*, 1 if the individual is male), the individual's primary language (*nepali*, 1 if the individual speaks Nepali), head of household dummy (*hhead*, 1 if the individual is a household head), number of persons living in the household (*hsize*), the household's ethnic background regarding high-, middle-, and low-caste groups (*hcaste*, *mcaste*, and *lcaste*),[6] and first job dummy (*firstjob*, 1 if the individual is holding the first job).

Having children, marital status, health, and household income may affect the employment decision. In our analysis, we include the number of children below and above six years of age (*childltsix* and *childgtsix*, respectively), health status (*illness*, 1

[6] The highest-caste group, including Chhetri, Brahman (hill), Newar, Thakuri, Sanyasi, Kaytastha, Marwadi, Nurang, Bengali, and Koche.

if the individual suffers from a health problem), marital status (*married*, *widowed*, and *divorced*), and household income in the model (*hincome*). These variables are likely to have no effects on market earnings, but will affect the employment decision. The presence of children below six years of age may be a motivation, particularly for females, to choose unemployment or casual labor employment.

Employment status and average monthly earnings differ between urban and rural employees. Both males and females living in urban areas are more likely to be absorbed in regular employment than those living in rural areas. Specifically, female workers show higher casual employment in rural areas, where the number of casual workers is more than seven times that in regular employment. Similarly, regular workers of both genders living in urban areas are more likely to receive higher payment than those living in rural areas. However, for female casual workers, the difference in earnings between urban and rural areas is very small. This may encourage females in urban areas to either engage in regular employment or remain unemployed.

We also find gender differences in education levels. Males are more likely to be educated than females in every aspect. However, the years of schooling for female workers in regular employment are close to that of male workers. For example, on average, male workers in regular employment in rural areas are educated for 6.4 years, while their female counterparts are educated for 5.7 years.

4. Results and discussion

Table 2 reports the results of the logit estimation of the determinants for choice of employment status by males and females in urban and rural areas. The results show that marriage decreases the probability of females being employed in both areas. Contrarily, marriage encourages males to work; however, the probability of occupation favors regular employment in

Table 2
Logit estimations in determinants of occupation.

	Urban				Rural			
	Male		Female		Male		Female	
	Regular	Casual	Regular	Casual	Regular	Casual	Regular	Casual
schoolyear	0.03**	−0.23***	0.09***	−0.15***	0.04***	−0.20***	0.23***	−0.13***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
age	0.09***	−0.07	0.19***	0.12**	0.15***	0.06***	0.29***	0.11***
	(0.03)	(0.05)	(0.04)	(0.05)	(0.03)	(0.02)	(0.06)	(0.02)
age2	−0.00***	−0.00	−0.00***	−0.00***	−0.00***	−0.00***	−0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
nepali	0.20*	0.18	−0.23*	0.44**	0.16	0.38***	−0.58**	−0.10
	(0.11)	(0.16)	(0.13)	(0.17)	(0.12)	(0.09)	(0.23)	(0.09)
hhead	0.40***	1.34***	0.22	0.51**	0.39***	0.58***	0.67***	0.72***
	(0.14)	(0.24)	(0.17)	(0.20)	(0.14)	(0.11)	(0.23)	(0.10)
hsize	−0.06**	0.07	−0.06*	0.01	0.04	0.07***	0.08	−0.00
	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.06)	(0.02)
lcaste	0.33*	0.59***	0.31	1.15***	0.68***	0.95***	0.55**	1.31***
	(0.17)	(0.22)	(0.20)	(0.22)	(0.16)	(0.12)	(0.27)	(0.11)
mcaste	0.20	0.51***	−0.15	1.03***	−0.10	0.34***	−0.41*	0.53***
	(0.12)	(0.18)	(0.15)	(0.19)	(0.13)	(0.11)	(0.24)	(0.11)
childltsix	−0.14*	−0.32***	−0.03	−0.21	−0.13**	−0.22***	−0.75***	−0.25***
	(0.09)	(0.12)	(0.10)	(0.13)	(0.07)	(0.05)	(0.16)	(0.05)
childgtsix	−0.03	0.00	−0.12*	0.07	−0.09*	−0.10**	−0.16	0.06
	(0.06)	(0.08)	(0.07)	(0.08)	(0.05)	(0.04)	(0.10)	(0.04)
illness	0.14	−0.70***	0.00	−0.20	−0.33**	−0.32***	0.27	−0.04
	(0.14)	(0.24)	(0.17)	(0.21)	(0.14)	(0.10)	(0.21)	(0.09)
married	0.34*	0.29	−1.33***	−0.62*	0.17	0.83***	−1.32***	−0.80***
	(0.18)	(0.30)	(0.20)	(0.33)	(0.18)	(0.17)	(0.29)	(0.16)
widow	0.11	0.35	−0.47	0.05	−0.09	1.01***	−1.17**	−0.58***
	(0.51)	(0.63)	(0.34)	(0.46)	(0.47)	(0.29)	(0.52)	(0.22)
divorced	−0.70	1.51**	0.11	0.18	−0.61	1.27***	−0.54	−0.19
	(0.72)	(0.63)	(0.42)	(0.58)	(0.68)	(0.40)	(0.64)	(0.33)
hincome	0.00***	0.00***	0.00***	0.00	0.00***	0.00***	0.00**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	−1.49**	1.13	−3.42***	−3.58***	−3.58***	−1.14***	−7.68***	−2.51***
	(0.60)	(0.84)	(0.70)	(0.86)	(0.54)	(0.42)	(1.02)	(0.38)
N	1852	1305	2281	2090	2546	3491	4355	5317
Pseudo-R^2	0.10	0.23	0.13	0.13	0.10	0.15	0.19	0.10

Notes: Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

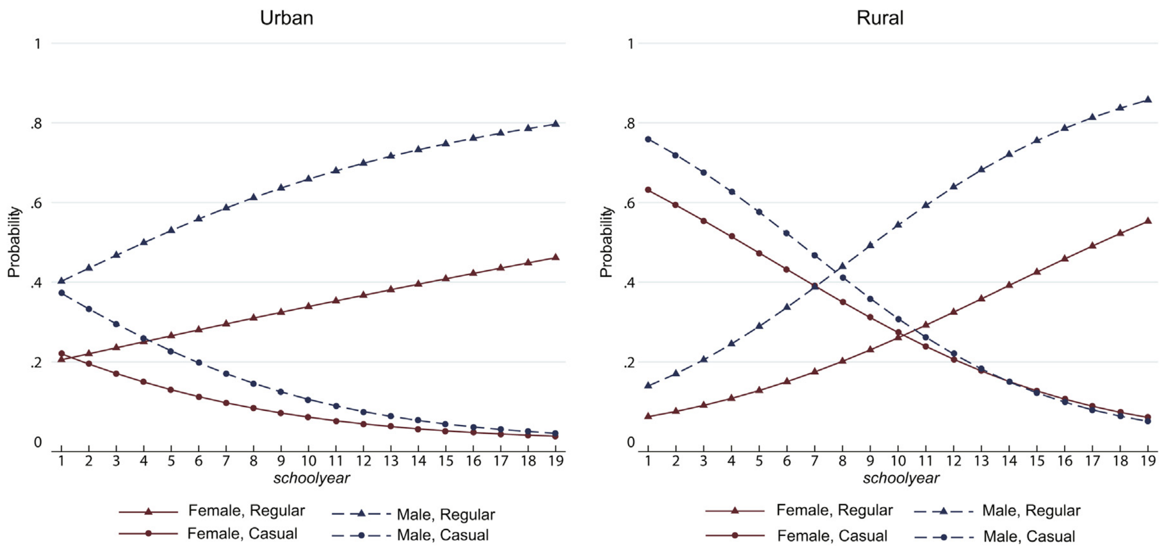

Fig. 1. Probability of occupation by years of education.

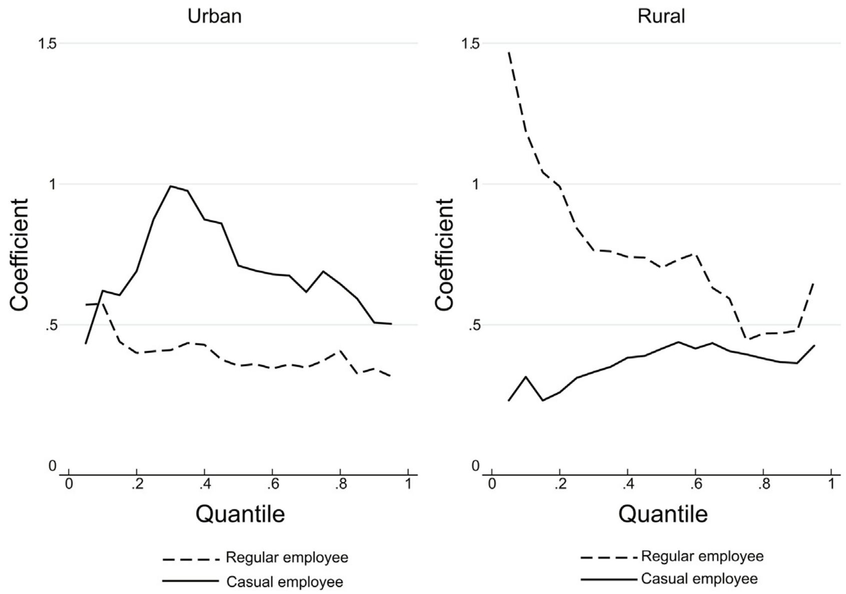

Fig. 2. Male wage premiums against wage distributions for each employment and area.

urban areas and casual employment in rural areas. Additional years of education increase the probability of being engaged in regular employment, while decreasing the probability of being engaged in casual employment in every regard. This indicates that well-educated people tend to choose regular employment or unemployment over casual employment.

Fig. 1 illustrates the marginal effect of years of education on occupational choice, estimated by gender based on Eq. (4), for urban and rural areas.[7] In both urban and rural areas, males have a higher probability of being in regular employment than females. In rural areas, residents (both males and females) with low to middle education levels have a higher probability of finding casual employment than regular employment. This indicates that the regular employment sector is more competitive in rural areas, especially for less-educated females. For instance, the probabilities of females with six years of education (graduated primary school) being in regular employment are approximately 15% and 28% for rural and urban areas, respectively.

[7] Note that the total number of possibilities of being in regular or casual employment do not equal 100; unemployment accounts for the balance.

Table 3
OLS estimates of wages for urban employment by gender and employment status.

	Regular				Casual			
	Pooled 1	Pooled 2	Male	Female	Pooled 3	Pooled 4	Male	Female
male	0.61***	0.51***			1.02***	0.89***		
	(0.06)	(0.06)			(0.12)	(0.13)		
schoolyear		0.08***	0.07***	0.09***		0.06***	0.05**	0.06
		(0.01)	(0.01)	(0.01)		(0.02)	(0.02)	(0.04)
age		0.07***	0.07***	0.07**		0.07**	0.09**	0.03
		(0.01)	(0.02)	(0.03)		(0.03)	(0.04)	(0.05)
age2		−0.00***	−0.00***	−0.00*		−0.00**	−0.00**	−0.00
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
nepali		0.15***	0.10*	0.26***		−0.13	−0.21*	0.03
		(0.05)	(0.05)	(0.10)		(0.11)	(0.13)	(0.21)
hhead		0.07	0.11	0.02		−0.01	0.03	−0.09
		(0.06)	(0.07)	(0.14)		(0.14)	(0.20)	(0.22)
hsize		−0.01	−0.02	−0.00		−0.02	−0.00	−0.04
		(0.01)	(0.01)	(0.02)		(0.03)	(0.03)	(0.05)
lcaste		−0.15*	−0.09	−0.37**		−0.22	−0.42**	0.06
		(0.08)	(0.10)	(0.15)		(0.15)	(0.18)	(0.25)
mcaste		−0.20***	−0.19***	−0.27**		−0.19	−0.20	−0.16
		(0.06)	(0.06)	(0.13)		(0.13)	(0.16)	(0.24)
firstjob		0.74***	0.67***	1.01***		1.14***	1.26***	0.98***
		(0.08)	(0.09)	(0.16)		(0.12)	(0.14)	(0.20)
Intercept	8.49***	5.71***	6.40***	5.20***	6.67***	5.09***	5.65***	5.74***
	(0.06)	(0.27)	(0.30)	(0.55)	(0.09)	(0.60)	(0.77)	(1.08)
N	1260	1260	857	403	589	522	310	212
adj. R^2	0.079	0.382	0.316	0.366	0.110	0.340	0.288	0.126

Notes: Robust standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Next, we observe gender differences in the wage distributions. In Fig. 2, we plot the “male wage premium” against quantiles of wage distributions. The figure plots the coefficients of males from the conditional wage quantile regressions based on Eq. (1). The dependent and explanatory variables are the same with regressions reported in Tables 3 and 4 (explained later in detail). There is a larger gender wage gap for casual employees than for regular employees in urban areas. On the contrary, in rural areas, the gender wage gap for regular employees is wider at every percentile of the distribution than for casual employees. Furthermore, in rural areas, we find the largest gap at lower wage levels. The gap for rural workers at the 10th percentile of the wage distribution is about 120%, while for casual employees, it is about 32%. For urban workers, these figures are about 58% and 62%, respectively.

Table 3 reports the results of the OLS regressions from Eq. (1). The dependent variable is the log wages along with the control variables by regular and casual employment for urban employees. The simplest regression results in “Pooled 1” and “Pooled 3” in Table 3 indicate that, on average, male workers earn about 61% and 102% more in regular and casual employment than female workers do, respectively. After controlling for individual characteristics, the male wage premium shrinks to 51% for regular and 89% for casual employment, as reported in “Pooled 2” and “Pooled 4” in Table 3.

Similarly, Table 4 reports the results of the OLS regressions for rural employees. The male wage premiums are 98% for regular and 62% for casual employees. Surprisingly, this premium increases to 109% for regular and 68% for casual employment after controlling for individual characteristics. These results imply that wages of female workers is low, even when they have higher education attainment than male workers do. In other words, rural females need better characteristics than males to find regular employment. This indicates that female workers are subject to discrimination in the wage market.

Tables 3 and 4 also report the results of the separate wage regressions for male and female workers under “Male” and “Female,” respectively. The returns on education are higher for regular workers than for casual workers for both genders. The returns on education are positive for regular employment, and its effect is stronger for female workers: 7% for males and 9% for females in urban areas, and 8% for males and 11% for females in rural areas. However, the effect of education shrinks for casual employees: 5% for males and 6% for females in urban areas, and 1% for males and 0% for females in rural areas. This indicates that accumulation of human capital (such as years of schooling) does not help improve productivity in casual work in rural areas. This is because most workers in this sector are hired for unskilled, manual labor, such as agricultural work.

The wage difference by caste group is also worth noting. Although not all coefficients are statistically significant, the coefficients of middle- and low-caste groups are negative, except for casual employees in rural areas.

Table 5 reports the results of wage decomposition at selected quantiles ($q = 0.10, 0.25, 0.50, 0.75, 0.90$) and at the mean. The results of regressions based on selectivity-adjusted estimates are also reported in the last column of each component. In the decomposition estimations, we find that gender wage gaps for regular employees at means could be explained by total

Table 4
OLS estimates of wages for rural employment by gender and employment status.

	Regular				Casual			
	Pooled 1	Pooled 2	Male	Female	Pooled 3	Pooled 4	Male	Female
male	0.98***	1.09***			0.62***	0.68***		
	(0.13)	(0.12)			(0.04)	(0.05)		
schoolyear		0.09***	0.08***	0.11***		0.01	0.01	−0.00
		(0.01)	(0.01)	(0.03)		(0.01)	(0.01)	(0.02)
age		0.11***	0.12***	0.14*		0.03***	0.05***	0.00
		(0.02)	(0.03)	(0.07)		(0.01)	(0.02)	(0.02)
age2		−0.00***	−0.00***	−0.00*		−0.00***	−0.00***	−0.00
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
nepali		0.16	0.05	0.48**		−0.14***	−0.10*	−0.24***
		(0.10)	(0.11)	(0.24)		(0.05)	(0.06)	(0.08)
hhead		−0.32***	−0.38***	−0.33		−0.11**	−0.13	−0.06
		(0.10)	(0.10)	(0.28)		(0.05)	(0.08)	(0.08)
hsize		−0.03*	−0.02	−0.07		−0.02**	−0.03**	−0.01
		(0.02)	(0.02)	(0.04)		(0.01)	(0.01)	(0.01)
lcaste		−0.03	−0.04	−0.08		0.21***	0.18**	0.23**
		(0.13)	(0.13)	(0.33)		(0.06)	(0.08)	(0.10)
mcaste		0.09	0.03	0.20		0.07	0.11	−0.03
		(0.11)	(0.11)	(0.27)		(0.07)	(0.08)	(0.10)
firstjob		0.63***	0.62***	0.72***		0.71***	0.80***	0.55***
		(0.08)	(0.08)	(0.22)		(0.05)	(0.06)	(0.07)
Intercept	7.48***	4.66***	5.82***	4.19***	6.43***	5.93***	6.32***	6.46***
	(0.13)	(0.48)	(0.49)	(1.37)	(0.03)	(0.22)	(0.30)	(0.34)
N	920	920	761	159	3282	2827	1706	1121
adj. R^2	0.076	0.292	0.229	0.255	0.064	0.149	0.097	0.082

Notes: Robust standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

endowment effects in 0.11 out of 0.61 cases for urban areas and in -0.12 out of 0.98 cases for rural areas, while the unexplained effects account for 0.51 and 1.10 cases for urban and rural areas, respectively. This means that, at mean, gender wage discrimination is much larger for rural females. In addition, the endowment effect is negative in rural areas, implying that rural females in regular work have better characteristics than male workers in terms of wages received. This might be attributable to the fact that females in regular work in rural areas tend to belong to the high-caste group.

The discrimination (unexplained) effects were much higher for rural workers at the mean and other selected quantiles. This indicates that in rural areas, female workers engaged in regular work face higher discrimination at every quantile of wage compared with their counterparts in urban areas. Furthermore, most endowment effects in rural employees have negative signs. The endowment advantage for females tends to be higher at lower quantiles of the wage distribution. This means that although female workers have better characteristics for earning, at lower wage quantiles, they face high discrimination. This implies that getting regular work is an intensely competitive activity for rural females.[8] This finding is consistent with those shown in Fig. 1.

Although the discrimination effect remains in the casual labor market, it is mitigated in rural areas. The gender wage gaps for casual employees can be explained by the endowment effects of 0.30 out of 1.16 cases for urban areas and −0.09 out of 0.61 cases for rural areas. The wage gap for casual employees was much higher for urban employees at each quantile, which also had the unexplained effect as the key driver.

In the decomposition of the selectivity-adjusted estimates, which added the selectivity bias effects estimated from Eq. (4), large selection effects appear for regular employees. This means that unobservable characteristics captured by the inverse Mill ratio would increase the gender wage gap for regular employees.[9] In the first stage of Heckman's (1979) model, the controlled factors are assumed to affect employment participation. The results for the first-stage probit regression are reported in Table A1. Many studies have found that marital status and having children are important determinants of

[8] It might be difficult to observe a causal interpretation in standard wage decomposition estimations because group membership is endogenous and observed covariates are influenced by omitted variables (Huber, 2015). Furthermore, Kunze (2008) stated that endogeneity issues lead to confounding of the effects of human capital variables on wage gap analyses.

[9] We also simulate the gender wage gap by controlling the sample selection for other quantiles. The results are presented in Figs. A1–A3. Unfortunately, results for urban women in casual work could not be obtained because of the discontinuous wage distribution. The results show that unexplained wage gaps were mitigated for women working in regular and casual work when selectivity bias is controlled. These results are consistent with our finding reported in Table 5. This might imply the possibility that gender wage gaps are attributed to opportunities of finding work.

Table 5
Mean and quantile decompositions.

Urban employees

	Regular							Casual						
	$q = 0.10$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$	OLS mean	selective corrected mean	$q = 0.10$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$	OLS mean	selective corrected mean
Difference in observed wage	0.97	0.71	0.60	0.37	0.37	0.61		1.27	1.48	1.36	1.03	0.79	1.16	
Endowment effects														
schoolyear	0.08**	0.09***	0.11***	0.12***	0.08***	0.10***	0.09***	0.11	0.13*	0.99**	0.16	0.04	0.09**	0.13**
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.11)	(0.07)	(0.05)	(0.03)	(0.41)	(0.04)	(0.06)
Total	0.07	0.18***	0.16***	0.14***	0.14***	0.11**	0.14***	−0.23	−0.14	−0.03	−0.00	0.16*	0.30**	−0.06
	(0.09)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.28)	(0.19)	(0.14)	(0.10)	(0.09)	(0.12)	(0.12)
Discrimination effects														
Total	0.91***	0.53***	0.45***	0.24***	0.22***	0.51***	−0.37	1.50***	1.62***	1.39***	1.03***	0.63***	0.86***	0.34
	(0.15)	(0.10)	(0.07)	(0.07)	(0.08)	(0.06)	(0.26)	(0.36)	(0.28)	(0.20)	(0.17)	(0.15)	(0.15)	(0.78)

Rural employees

	Regular							Casual						
	$q = 0.10$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$	OLS mean	selective corrected mean	$q = 0.10$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$	OLS mean	selective corrected mean
Difference in observed wage	1.47	1.25	0.98	0.72	0.35	0.98		0.47	0.52	0.59	0.72	0.71	0.61	
Endowment effects														
schoolyear	0.08	0.07*	0.07*	0.07*	0.04	0.06*	0.07*	−0.01	0.01	0.01	0.00	0.04*	0.02	−0.02
	(0.05)	(0.05)	(0.04)	(0.04)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Total	−0.48***	−0.27***	−0.10	−0.01	−0.05	−0.12*	−0.14**	−0.14*	−0.09	−0.12**	−0.10**	−0.06	−0.09**	−0.14***
	(0.14)	(0.09)	(0.07)	(0.07)	(0.05)	(0.07)	(0.07)	(0.08)	(0.07)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
Discrimination effects														
Total	1.95***	1.52***	1.08***	0.74***	0.40***	1.10***	−0.62	0.61***	0.61***	0.72***	0.81***	0.77***	0.69***	0.62**
	(0.31)	(0.22)	(0.16)	(0.16)	(0.14)	(0.13)	(0.79)	(0.11)	(0.10)	(0.07)	(0.07)	(0.08)	(0.06)	(0.24)

Note: OLS quantile decomposition estimations are reported.
Bootstrapped standard errors are in parentheses with 1000 replications.
The results of the first stage for selective corrected mean estimations are reported in Table A1.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

employment decisions, especially for women. For example, married women and women with children are less likely to find job opportunities in developing countries due to cultural effects or household responsibilities (De Giusti & Kambhampati, 2016; Lokshin, Glinskaya, & Garcia, 2004; Miles, 2002). The coefficient of marital status is negative for women and positive for men in regular work. This indicates that married women are less likely to engage in work, while married men tend to engage in regular work.

Contrary to expectations, the coefficients of having children are not statistically significant (Table A1). Children do not always reduce their parents' possibility of employment participation, because older children may help their parents in household chores (Webbink, Smits, & de Jong, 2012). We also found that the coefficient variable of *lcaste* is negative in every estimation (Table A1). This indicates that individuals from the low-caste group are likely to engage in both regular and casual work. This might imply that caste discrimination is weak with respect to engaging in work. However, this does not mean there is no job discrimination against the low-caste group in Nepal's labor market.

For some estimations, the endowment effect became negative and statistically significant, meaning that the female workers have positive characteristics in the wage market. The unexplained effects remain positive in casual work, meaning that females face unfair wage structures. This result indicates that gender wage discrimination remains in Nepal, while some studies found that the gender wage gap declined in Asian countries such as South Korea, Vietnam, Taiwan, and Thailand (Bishop, Grodner, Liu, & Chiou, 2007; Monk-Turner & Turner, 2004; Nakavachara, 2010; Pham & Reilly, 2007). In addition, our result contradicts related findings from Nepal and Bangladesh. Koirala (2007) found that a gender wage gap in manufacturing industries in Nepal decreased during 1992–2002 by using individual firm data. He pointed out that the difference in educational attainment leads to the gender wage gap. Our results show that a gender gap in the labor market still remains, especially for rural females even with controlled educational attainment. Furthermore, Ahmed and

McGillivray (2015) found that the gender wage gap decreased with an improvement in female educational qualification and a decline in the discrimination against women during the liberalization in the last decade. Furthermore, they concluded that higher human capital accumulation by females was the main driver for changes in labor market conditions during 1999–2009.[10]

5. Conclusion

In this study, we investigated the gender wage gap in the urban and rural labor markets in Nepal. The estimation results suggest that rural females face disadvantages in both job opportunities and wage payments due to the unexplained effects. It is difficult for rural females to find regular work even if they are well educated. Furthermore, those who find regular employment in rural areas face significant gender discrimination in wages. This might discourage parents from providing education to their daughters. On the other hand, the marginal effects of years of education on finding regular employment and getting higher wages are higher for rural females. Therefore, it is important to encourage parents in developing regions to educate their daughters.

Our Oaxaca–Blinder estimation results suggest that discrimination effects vary depending on employment status and areas. This may be attributed to the differences in industrial structures between regions. In rural areas, casual agricultural work is the main job opportunity for both men and women, while in urban areas, agricultural work is primarily restricted to women. Other types of work, such as construction and manufacturing, can offer casual employment opportunities to males in urban areas. In fact, 41% of males in casual work are engaged in the agricultural sector in rural areas, while only 17% are involved in agricultural work in urban areas. This difference may have contributed to the wide gender wage gap for casual employees in urban areas.

Another explanation for this gap is that the reservation wage for females in urban areas exceeds the potential wages from casual work. Thus, the ratio of females choosing unemployment is higher in urban areas. This implies that females with better characteristics tend not to get involved in casual work if they cannot find regular employment.

This study has some limitations. One issue is that the estimated gender differences in market wages and employment possibilities may capture omitted differences besides discrimination. Although we tried to capture differences according to regular and casual employment status, other types of occupation statuses, such as being involved in the industrial sector, may have differing effects on wages. Future analyses should aim to capture other sources of gender discrimination in each area and industry.

Another issue is that several household- and individual-level variables to control for wages were excluded from our estimates due to data limitations. Therefore, we cannot fully rule out the possibility of bias that may be introduced by unobserved household and individual characteristics, or the portion of unexplained components. For example, here, we used the individual's age as a proxy of job experience. However, Huber and Solovyeva (2018) found that the unexplained gender wage gap increased or decreased when ignoring or controlling for years of work. Higher educational attainment and job experience is a kind of trade-off, as long as the individual's age remains the same. Therefore, omitting job experience might misrepresent the effects of education.

Compliance with ethical standards

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Conflict of interest

None.

Appendix A.

We show the estimation results of quantile decomposition with a sample selection problem by employing the achado-Mata-Melly decomposition (Machado & Mata, 2005; Melly, 2005) with the quantile regression with sample selection (Arellano & Bonhomme, 2017) in Figs. A1–A3. We first estimate the conditional quantile function of group g, $F^{-1}_{y|x,g} = x_i\beta^g(\tau)$ for any τth quantiles of y by following Arellano and Bonhomme (2017). We first recover the group g's distribution of y as $\sum_\tau\sum_{i\in g}x_i\beta^g(\tau)$, then, we construct the counterfactual distribution as $\sum_\tau\sum_{i\in g}x_i\beta^{g'}(\tau)$ where $g\neq g'$. The estimation results are shown in Fig. A1 for urban females in regular work, Fig. A2 for rural females in regular work, and Fig. A3 for rural females in casual work.

[10] In Bangladesh, the rates of completion of secondary education have improved substantially: 0.253 for males and 0.130 for females in 1999, and 0.443 for males and 0.345 for females in 2009.)

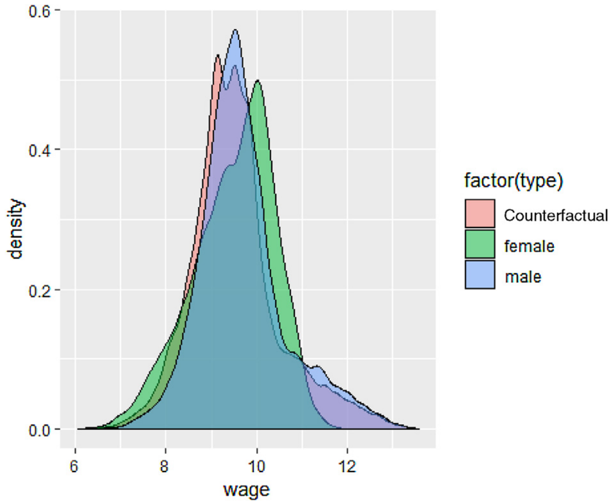

Fig. A1. Counterfactual distribution: urban female with male characteristics in regular works.

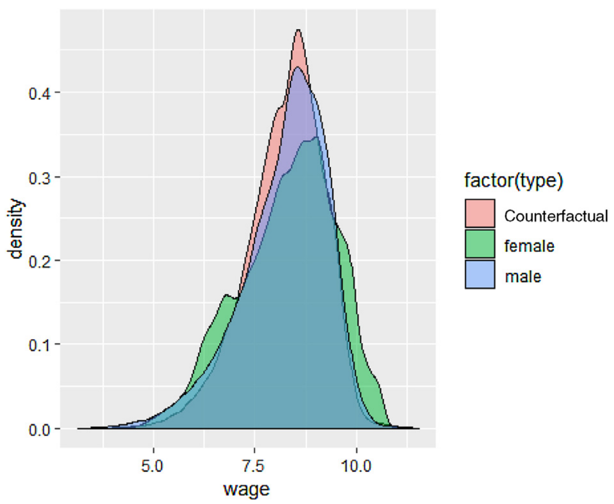

Fig. A2. Counterfactual distribution: rural female with male characteristics in regular work.

Fig. A3. Counterfactual distribution: rural female with male characteristics in casual work.

Table A1
First-stage probit estimation of selective corrected model for Table 5.

	Urban				Rural			
	Regular		Casual		Regular		Casual	
	Male	Female	Male	Female	Male	Female	Male	Female
schoolyear	0.02***	0.05***	−0.13***	−0.08***	0.03***	0.11***	−0.12***	−0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
age	0.05**	0.09***	−0.05*	0.05**	0.08***	0.12***	0.04***	0.06***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
age2	−0.00***	−0.00***	0.00	−0.00***	−0.00***	−0.00***	−0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
nepali	0.05	−0.14	−0.03	0.01	−0.04	−0.28***	0.12**	−0.15***
	(0.08)	(0.09)	(0.11)	(0.10)	(0.08)	(0.11)	(0.06)	(0.05)
hhead	0.25***	0.09	0.76***	0.28**	0.22***	0.26**	0.34***	0.41***
	(0.09)	(0.09)	(0.13)	(0.11)	(0.08)	(0.11)	(0.07)	(0.06)
hsize	−0.03*	−0.05**	0.04	0.01	0.02	0.03	0.05***	−0.00
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)
mcaste	−0.10	−0.41*	0.06	−0.18	−0.19	0.06	0.08	0.22*
	(0.18)	(0.25)	(0.21)	(0.24)	(0.18)	(0.25)	(0.14)	(0.12)
lcaste	0.35***	0.48***	0.50***	0.82***	0.49***	0.41***	0.65***	0.87***
	(0.13)	(0.13)	(0.16)	(0.14)	(0.10)	(0.14)	(0.08)	(0.07)
childltsix	−0.09*	0.02	−0.16**	−0.10	−0.07*	−0.31***	−0.13***	−0.14***
	(0.05)	(0.06)	(0.07)	(0.07)	(0.04)	(0.07)	(0.03)	(0.03)
childgtsix	−0.01	−0.02	0.02	0.05	−0.04	−0.05	−0.06**	0.04*
	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)	(0.05)	(0.02)	(0.02)
illness	0.09	0.01	−0.40***	−0.07	−0.20**	0.14	−0.20***	−0.03
	(0.09)	(0.09)	(0.14)	(0.11)	(0.08)	(0.10)	(0.06)	(0.05)
married	0.23**	−0.77***	0.19	−0.29*	0.12	−0.61***	0.49***	−0.47***
	(0.11)	(0.12)	(0.17)	(0.18)	(0.11)	(0.15)	(0.10)	(0.09)
widow	0.09	−0.28	0.31	0.05	−0.05	−0.56**	0.59***	−0.34***
	(0.31)	(0.19)	(0.35)	(0.24)	(0.26)	(0.26)	(0.17)	(0.13)
divorced	−0.41	0.03	0.81**	0.12	−0.29	−0.25	0.73***	−0.11
	(0.43)	(0.26)	(0.39)	(0.33)	(0.37)	(0.32)	(0.23)	(0.19)
hincome	0.00***	0.00***	0.00***	0.00	0.00***	0.00**	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	−0.77**	−1.78***	0.88*	−1.70***	−1.92***	−3.68***	−0.60**	−1.37***
	(0.37)	(0.39)	(0.50)	(0.45)	(0.32)	(0.47)	(0.25)	(0.22)
N	1852	2281	1305	2090	2546	4355	3491	5317
Chi-squared	255.13	300.92	347.94	203.59	338.99	276.18	743.13	594.10

Notes: Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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