Inequality in Earnings Among Religious Groups in Bangladesh[*]

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Abstract

Few researchers have examined the nature and determinants of wage inequality among religious groups, and none have undertaken this in the context of multi-religious societies such as Bangladesh. This paper aims to address this void in the literature by analysing the wage gap between two main religious groups in Bangladesh: Muslim and Hindu, at the mean and over the wage distribution during 1999-2009, a time span in which the country experienced the emergence of Islamist political formations as well as stable and high economic growth following economic liberalisation since 1990s, an improving labour market and widening of career opportunities for the minority. Applying unconditional quantile regression models, the paper documents a significant wage advantage for Hindu workers aged 15-65 across the wage distribution. The key driver of this reverse wage gap was an improvement in educational qualifications among Hindus. Another factor was that the extent of discrimination against Hindu wage workers disappeared completely over the period 1999-2009, especially at the lower end of the distribution. The paper also demonstrates that controlling for selection into employment does not eliminate this estimated Hindu wage advantage. The reverse wage gap is now smaller, suggesting that the observed reverse wage gap is likely to be overestimated if selection bias into employment is ignored.

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Key words: Religion, Hindu, Muslim, Wage Inequality, Discrimination, Selection, Bangladesh

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1. Introduction

Bangladesh is a predominantly Muslim-populated state. But it has both ethnic and religious minorities. In most instances the former belong to the latter category as well. Among the non-Muslims, Hindus are the most significant minority both in terms of numbers and also for political and historical reasons. According to the population census of 1991, Muslims formed 88.3 percent, while Hindus constitute 10.5 percent of the Bangladeshi population, by 2011, these numbers had increased to 90.3 percent for Muslims, but decreased to 8.53 percent for Hindus (BBS 1993; BBS 2012). These figures are alarming suggesting that the Hindu population in Bangladesh are declining. The constitution of Bangladesh safeguards equal rights and opportunity for all people irrespective of any race, caste, religion, gender and place of birth (article (1) of the 1972 Constitution of Bangladesh); however, state's bias in the Constitution and its reluctance to address human rights violations and discrimination against minorities led Hindu community to a huge migration to India and other places.

Proponents believe that discrimination towards the Hindu Community in Bangladesh is both visible and hidden. Hindu minorities are often at the bottom of the social hierarchy and, therefore, have the least political recourse. For example, Hindu representation in parliament in 1954 (pre-independence era) was nearly 25 percent, it declined to less than 3 percent at later stages (Sarkar 2008). Also because of religious beliefs and state security, Hindus are generally not appointed in Defence and Foreign Services of Bangladesh and their representation in administrative position is nearly non-existent. The employment disadvantages of Hindus will likely to generate a larger wage penalty against the minority group. Ironically, although Hindu minorities fare less in employment hierarchy in the Bangladesh economy than the majority Muslim population, they seem to do as well or even better in terms of educational attainment and training. Part of the explanation may be related to persecutions of Hindus over time that made them feel insecure regarding nonhuman assets which can be easily expropriated (e.g., through the Vested Property Act) and that this discrimination has encouraged Hindus to favour more portable and inalienable investments such as human capital. This hypothesis suggests that, other things the same, Hindus invest relatively more in schooling, and less in other assets, but this would

lower return to the human capital of Hindus.[2] Therefore, the alternative explanation is Hindus may learn more in school because of supplemental training received in the home or in the Hindu community prior to or concurrent with schooling. The relative success of Hindus in human capital acquisition (especially compared with the Muslim) will allow them to assimilate in the labour market; hence, it will probably help in reducing wage gaps with the Muslim. Our intent in this paper is to test this hypothesis by examining wage inequality between Muslim and Hindu workers during 1999-2009, a time span in which the country experienced the emergence of Islamist political formations as well as stable and high economic growth following economic liberalisation since 1990s, an improving labour market and widening of career opportunities for the minority.[3] The mix of economic and political events and trends make the period of our analysis interesting.

We analyse and decompose the Hindu-Muslim wage gaps, using a framework integrating differences in human capital characteristics (the *endowment effect*) and labour market discrimination (the *discrimination effect*). The latter effect falls under the rubric of *minority status*, which asserts that disparities in earnings between the dominant group and the minority group could reflect extensive socio-historical differences of which inequality in acquisition of human capital or training is only a part; hence, differences would persist even with parity in other factors. Past research on the racial wage gap generally identified this as *discrimination* (see references in Sandefur and Scott 1983).[4] However, some social scientists have suggested that at least part of what is typically regarded as the effect of discrimination might be due to cultural differences between the minority group and the dominant group. But Hindus in Bangladesh are native-born and they share the same *culture* as Muslims, that is, they are

[2] For exchange on this point, see Chiswick (1983) who suggested that Jews have cultural taste for schooling because of a fear that their nonhuman assets may be vulnerable to expropriation.

[3] The government enacted the Labour Act in 2006, the most comprehensive labour law since Bangladesh's independence. The act introduced several new pieces of legislation, such as penalty for unfair labour conduct, increased minimum wage in the ready-made garments industry, an extension of maternity leave benefits and child care facilities at workplace, among others. In addition, over the period 1999-2009, the gap in average wages between men and women decreased by 31 percent (Ahmed and McGillivray 2015).

[4] Also particular care must be taken when interpreting the term discrimination throughout the paper. This is because it includes the effect of labour market discrimination, unobservable variables (for example, motivation) and omitted variables. The latter affect might mean that if there is any sort of omitted variable that has a positive effect on wages, and if Muslims are more highly endowed with this variable, then the results from the decomposition would overestimate discrimination. Alternatively, if some of the factors in the model are themselves affected by discrimination, then the analysis could well underestimate discrimination. For example, if Hindus have less access to the types of schooling deemed more valuable by the market, then the decomposition may well underestimate discrimination.

usually characterised as *Bengali*. The difference in the labour market outcomes may therefore be attributed mainly to differences in religion and not to *Bengali culture*. In that sense, differences in labour market outcomes between Muslims and Hindus may persist even if Hindus adopt the majority culture. For example, Hindus by far are the larger religious minority group in Bangladesh. Therefore, the Muslim-Hindu competition is probably more common than the Muslim-other group competition. This could lead to more discrimination against Hindus than against the other religious group. Yet the reverse can also happen. In general, there is no specific affirmative action policies on the ground of religion in Bangladesh; but since market discrimination appears to have declined during 1999-2009 (Ahmed and McGillivray 2015), it could have contributed to remove barriers between the dominant group and the minority group.

When estimating wage gaps, selection into employment is a key concern. If all Muslims work but a disproportionate number of well-educated, potentially *high-earning* Hindus choose not to work for pay, the estimated observed wage gap will be higher than the true gap that would have been observed had all Hindus been working. On the other hand, we can speculate that since skill premium increased over the period 1999-2009 (Ahmed and McGillivray 2015), it draws more highly educated Hindus (more often than not, Muslims) into employment while driving less educated Hindus out of employment. Hence, the observed wage gap between Muslims and Hindus will be smaller than the gap that we would see if all Muslims and Hindus were employed. That is, selection issues cannot be ignored if one aims to identify the true extent of the wage gap.

This paper contributes to the literature in three further respects. First, to our knowledge, this is the only study that examines wage differentials by religion in Bangladesh. Though scholars have frequently noted large wage differentials between males and females in the Bangladesh labour market (Salway et al. 2003; Akter 2005; Hossain and Tisdell 2005; Kapsos 2008; Ahmed and Maitra 2010; Ahmed and McGillivray 2015; Ahmed and Maitra *forthcoming*), there has been comparatively no such research by religion. Therefore, little hard evidence is available for policy makers to assist the minority group. Second, recent evidence from both developed and developing countries indicates that the wage gap between Muslims and non-Muslims varies over the entire wage distribution (Levanon and Raviv 2007; Longhi et al. 2013); however, the contribution of these studies was limited since the findings derived

from these studies did not account for selection bias into employment. In this paper, we adjust for selection and perform decompositions both at the mean and at specific quantiles ($\tau = 0.10, 0.50, 0.90$) of the wage distribution. We start by conducting the Oaxaca-Blinder type decomposition approach based on newly developed unconditional quantile regression models (Firpo et al. 2009).[5] To address the issue of selection into employment, we use the approach as in Ahmed and Maitra (*forthcoming*). The selection adjustment primarily entails imputing wages for non-participants in a given year based on their observable characteristics, using the repeated imputation method (Rubin 1987). More specifically, we perform wage imputations for non-participants by making simple assumptions about the position of imputed wage observations with respect to the median. We then decompose the wage gap between Muslims and Hindus into *endowment* and *discrimination* effects at the mean and at quantiles of the imputed wage distributions and assess the impact of selection into employment by comparing estimates for the base sample with estimates obtained for a sample enlarged with wage imputation.[6]

Finally, we use the most recent and a large-scale database–the Labour Force Survey (LFS) datasets for 1999, 2005 and 2009.[7] This dataset provides more detailed information on individual wages, socio-economic and family characteristics by religion. Despite its advantages, the dataset has been under-utilised. The notable exceptions are Ahmed and Maitra (*forthcoming*) and Ahmed and McGillivray (2015); however, their analysis of the LFS dataset was restricted to identifying wage differentials by gender rather than quantifying the wage differential by religion.

In the next section, we discuss the historical background and related literature. In section 3, we discuss the estimation framework. Section 4 describes the relevant data and outlines labour market characteristics and wages of Muslim and Hindu workers. Section 5 presents our empirical findings and Section 6 concludes the paper.

[5] The advantage of the unconditional quantile regression over the traditional quantile conditional quantile regression of Koenker and Bassett (1978) is that the estimated coefficients are explained as the impact of changes in the distribution of explanatory variables on the targeted quantiles of the unconditional marginal distribution of the dependent variable. Therefore, we can apply the Oaxaca-Blinder decomposition method directly to the estimation results obtained from the unconditional quantile regression.

[6] Recently this is the most common approach to address selection out of work (see McHenry and McInerney 2014; Albrecht et al. 2015).

[7] We would like to use data for 2002 as well. However, religious adherence is not included in the 2002 survey questionnaire. The 2009 is the most recent year of data available at the time of writing.

2. Historical Background and Related Literature

Religious cleavage provided the main dynamics of politics in the Indian sub-continent in the first half of the twentieth century. Historically, the relationship between Muslim and Hindu populations in this sub-continent is rife with conflict and tension. The partition in 1947 came in the wake of large scale Muslim-Hindu riots. The partition of Pakistan in 1971 was accompanied by an ideological revolution in former East Pakistan (now Bangladesh) which upheld secularism as against the Islamic ideology of Pakistan. Proponents indicate that Hindus from East Pakistan bore a disproportionate brunt of Pakistani Army repression– nearly 2.5 million Hindus were killed during the Bangladesh Liberation War in 1971.[8] Given the aftermath of Hindu genocide, the first constitution of Bangladesh has declared secularism and equality of all citizens irrespective of religious identity during the Awami League regime–the first national government of Bangladesh, which has been considered to be the most secular and favourably disposed toward minority rights among Bangladesh's major political parties. However, the constitutional provision for secularism and rights of non-Muslims remain controversial until today. Hindu minorities in particular persecuted with state sanction through the 1972 Enemy/Vested Property Acts, which permitted the seizure of Hindu citizens' property with impunity. An estimated 30 percent of Bangladesh's Hindu population has been directly affected by the law,[9] which appears to be correlated with emigration to India. Moreover, Hindus have been iconised as the *oppressors* largely because the broader public opinion continues to conflate Hindus with India.

The constitutional provision has been abandoned during the regime of the Bangladesh Nationalist Party (BNP). Islam was declared as the state religion, taking the country a significant step away from its secular foundation. BNP and its Islamists Coalition Partners ruled Bangladesh for a total of 14 years and three terms since its birth in September, 1978 (1978-1982, 1991-1996, and 2001-2006). The pro-Islamic BNP party and its allies was widely blamed for human rights violations and discrimination against Hindus. The most vivid example–the Enemy/Vested Property Acts was repealed in 2001, but the government has not made significant progress to reinstate property to those from whom it had been

[8] Hindu Genocide in East Pakistan: http://www.hindunet.org/hindu_history/modern/hindu_bangla.html, for detail.
[9] Hinduism in Bangladesh: https://en.wikipedia.org/wiki/Hinduism_in_Bangladesh, for detail.

seized. In addition, riots on medium or smaller scales targeting Hindus have taken place periodically in order to encourage them to emigrate in order to seize their property.

The 2008 elections brought to power the Hindu-backed Awami League. The ruling party restored the first constitution of Bangladesh. The new government included three non-Muslims among the 38 ministerial positions (USCIRF 2010). Members of minority communities were also appointed to other senior government and diplomatic positions. The government also declared to repeal all laws that discriminate against the minority group and uphold equality of opportunity and equal rights for all citizens. The Awami League won the second term in 2014 general election.

We can therefore speculate that as barriers to entering specific occupations are removed, the minority group entering the labour force are likely to have a wider choice of jobs and training opportunities that enforce the improvement in economic well-being such as earnings among religious groups. However, there are relatively no studies that focus on this issue in the context of Bangladesh.

On the other hand, wage differentials on the ground of religion have been examined largely in the context of the United States and Canada. The general consensus of this body of literature is that religion may play an important role in determining one's values, skills, endowments and goals, which in turn influence earnings and the rate of return to human capital. For example, on the connection between religious values and the return to human capital, economic demographers have frequently asserted that Roman Catholics face additional psychic costs of birth control, and this lowers the price of numbers of children, the resulting larger family size would tend to reduce investment in each child and raise the marginal returns on such investments. Following the paper by Gockel for the United States, a number of studies generally confirmed this hypothesis (Taubman 1975; Greeley 1976; Tomes 1984). Exceptions are studies by Featherman (1971) and Roof (1981) for the United States and Meng and Sentence (1984) for Canada. The former found no significant difference, the latter found that Jews have substantially higher returns from schooling than Protestants and the Catholics. This result has been also supported by most recent studies in the United States (Steen 1996; Burstein 2007; Chiswick and Huang 2008).

Proponents also believe that greater ability or human capital may increase the capacity to learn and retain religious tenets and this in turn would affect the return to human capital. Recent findings by scholars on Jews are generally consistent with such hypothesis. Chiswick (1983), for example, finds

that Jews receive higher incomes than non-Jews in the United States, after controlling for a variety of characteristics. The Jewish advantage over people of other religion has also been recorded in Canada. Richmond and Kalback (1980) find that Jews earn more than other individuals and the wage differential was entirely explained by higher levels of urbanisation and education. Tomes (1985) also showed that, Jews in Canada earned 12.7 percent more than the Protestants who, in turn, earned 5.1 percent more than people of all religious denominations.

A small number of studies now exists on the wage gap between Muslims and non-Muslims. Lindley (2002) in the UK and Levanon and Raviv (2007) in Israel found that Muslims earn considerably less than non-Muslims. More recently, Khattab (2015) and Longhi et al. (2013) found similar results for the UK. They show that the wage penalty for Muslims seems to be driven by the types of jobs that people are employed in, given their educational qualifications. This argument has recently been further confirmed by Brynin and Güveli (2012). They found that part of the wage gaps for Muslims is explained by their concentration in low-paid occupations in the UK. However, Bhaumik and Chakrabarty (2007) derived slightly different results for India, concluding that Muslim wage earners on average earn less than their Hindu counterparts and that differences are largely attributed to differences in educational attainment.

3. Empirical Framework

3.1 Firpo et al. Decomposition

In order to identify the underlying causes of the wage gap between Muslim and Hindu employees at the specific quantiles of the wage distribution, we perform the Oaxaca-Blinder decomposition based on unconditional quantile regression estimates.[10] Firpo et al. (2009) demonstrate that a corresponding Oaxaca–Blinder decomposition can be approximated for any distributional statistic (including quantiles). This method comprises two stages. In the first stage, distributional changes are divided into a wage structure effect (the *discrimination effect*) and a composition effect (the *endowment effect*). To decompose the wage gap into the two components mentioned previously, we produce a counterfactual

[10] A small but growing body of literature has adopted the unconditional quantile regression methodology to examine (and decompose) gender differences in wages across the wage distribution. Two representative papers in the context of Bangladesh are Ahmed and Maitra (*forthcoming*) and Ahmed and McGillivray (2015).

wage distribution, lnw_{ct}, which represents the distribution of wages of Muslim workers in employment if they had the same distribution of characteristics as Hindus. The counterfactual can be obtained by a re-weighting method (i.e., re-weight the distribution of workers in one group to control for composition).[11] This re-weighting method allows us to separate composition from wage structure effects. Specifically, the predicted wage differential $D_t(\tau)$ measured at quantile τ in period t (1999, 2005 or 2009) can be decomposed as follows:[12]

$$\begin{aligned} D_t(\tau) &= lnw_{mt}(\tau) - lnw_{ht}(\tau) \\ &= \underbrace{[lnw_{mt}(\tau) - lnw_{ct}(\tau)]}_{endowment\ effect} + \underbrace{[lnw_{ct}(\tau) - lnw_{ht}(\tau)]}_{discrimination\ effect} \end{aligned} \quad (1)$$

The first component of Equation (1) measures the wage gap due to differences in characteristics between Muslims (m) and Hindus (h) (the *endowment effect*) and the second component is the wage gap due to differences in returns to those characteristics (the *discrimination effect*). As discussed above, the counterfactual wage $lnw_{ct}(\tau)$ can be obtained by re-weighting. We define the re-weighting factor as:

$$\psi_{it} = \left[\left(1 - p(X_{it})\right)/p(X_{it})\right] \times [p/(1-p)] \qquad i = 1, \dots, n;\ t = 1999,2005,2009 \quad (2)$$

where $p(X)$ is the probability of being a Muslim employee conditional on various sets of wage covariates X. We can estimate these probabilities using probit models in which the dependent variable is a Muslim dummy; p denotes the proportion of Muslims in the full sample. This re-weighting factor then multiplies the observed wage distribution for Muslims to create a counterfactual wage distribution, $lnw_{ct}(\tau)$.

In the second stage, the two components of Equation (1) are further divided into two stages. The first stage of decomposition requires estimation of the re-centred influence function (RIF) regressions for each distributional statistic, which is the core of the Firpo et al. (2009) method. The authors show that one can obtain the average effects of explanatory variables on a distributional statistic (for example,

[11] The first step of the decomposition is semi-parametric because it does not assume any functional form for the wage distribution.

[12] In estimating gender wage gaps, wage equations $lnw_{ijt} = X'_{ijt}\beta_{jt} + \varepsilon_{ijt}$ (where j denotes males or females) are estimated separately for men and women in order to allow for different rewards by gender to a set of productive characteristics or endowments. A similar argument may apply to the wage gap between Muslims and Hindus. A Chow test (F-test) rejects the null hypothesis that explanatory variables have equal impacts on the wages rates of Muslim and Hindu workers for the three survey years. The Chow test statistic is 1.47 (p = 0.048) for the survey year 1999, 2.79 (p = 0.000) for the survey year 2005 and 3.08 (p = 0.000) for the survey year 2009.

wage quantiles) by running regression with original response replaced by the RIF of the statistics. The regression is known as the RIF regression. We run separate RIF regressions for lnw_m, lnw_h and lnw_c. The second stage of decomposition decomposes the wage gap into explained (the *endowment effect*) and unexplained components (the *discrimination effect*) at each quantile, as is usually done with the Oaxaca-Blinder decomposition. Specifically, the wage differential at quantile τ can be decomposed as follows:

$$D_t(\tau) = \left[\left(\bar{X}_{mt}\hat{\beta}_{mt}(\tau) - \bar{X}_{ht}\hat{\beta}_{ct}(\theta)\right) + \hat{R}_E(\tau)\right] + \left[\bar{X'}_{ht}\left(\hat{\beta}_{ct}(\tau) - \hat{\beta}_{ht}(\tau)\right) + \hat{R}_C(\tau)\right] \quad (3)$$

Here, $\bar{X}_{jt}$ $(j = m, h)$ is a vector of average characteristics of workers.[13] The first term $\left(\bar{X}_{mt}\hat{\beta}_{mt}(\tau) - \bar{X}_{ht}\hat{\beta}_{ct}(\tau)\right)$ represents the pure endowment effect, that is, the wage gap at the τ^{th} quantile due to endowment differentials.[14] The second term $\left(\hat{\beta}_{ct}(\tau) - \hat{\beta}_{ht}(\tau)\right)$ measures Muslim–Hindu differences in returns to labour market characteristics. Thus, $\bar{X'}_{ht}\left(\hat{\beta}_{ct}(\tau) - \hat{\beta}_{ht}(\tau)\right)$ represents the wage gap at the τ^{th} quantile due to the different returns (the *discrimination effect*). This is the wage difference that is due to differential reward for equal characteristics and is interpreted as a measure of the extent of actual discrimination in the labour market. $\hat{R}_E$ and $\hat{R}_C$ are the estimates of approximation errors corresponding to the *endowment effect* and the *discrimination effect*, which will appear in practice because of the first order approximations and the way in which the counterfactual wage distribution is constructed in RIF regression functions.[15] In practice, the approximation errors may be estimated as follows:

$$\hat{R}_E(\tau) = \left[lnw_{mt}(\tau) - lnw_{ct}(\tau) - \left(\bar{X}_{mt}\hat{\beta}_{mt}(\tau) - \bar{X}_{ht}\hat{\beta}_{ct}(\tau)\right)\right] \quad (4)$$

$$\hat{R}_C(\tau) = \left[lnw_{ct}(\tau) - lnw_{ht}(\tau) - \bar{X'}_{ht}\left(\hat{\beta}_{ct}(\tau) - \hat{\beta}_{ht}(\tau)\right)\right] \quad (5)$$

3.2 Selection into Employment

[13] The unconditional properties of the wage function can be obtained by averaging the wage function over X.

[14] In our analysis, we present and discuss the results corresponding to the case where the wage rates for Muslims are the reference category. This assumption is reasonable in our context, as the majority of the workforce in Bangladesh is Muslims.

[15] As discussed in Firpo et al. (2009), it is important to compute approximation errors in order to determine whether the linear model is well specified.

Wages are observed only for those who enter the labour force, and once they choose to work as employees. As selection into employment is not random, we account for possible selection bias by imputing a wage for those not employed. This is similar to the most recent work on Bangladesh that was done by Ahmed and Maitra (*forthcoming*).[16] This approach requires neither assumptions about the actual level of missing wages, which are typically required in the matching approach, nor arbitrary exclusion restrictions, which are often involved in sample selection correction models.

To perform wage imputation for non-participants, we rely on the observed characteristics of the non-participants, that is, we impute wages for the non-participants by assigning them the observed wages of employed individuals with matching characteristics (Juhn 2003). This method has the advantages of using all of the available information concerning the characteristics of the non-participants and taking into account uncertainty about the reason for the missing wage information.

This imputation is performed using Rubin's two-step repeated imputation technique (Rubin 1987). In the first step, using the sample of employed workers, we define a dummy variable I_{it} that is equal to 1 for an individual i in period t who is above the median of the observed wage distribution and 0 otherwise. We then estimate a probit model for I_{it} on a vector of variables X_{it} that are available for both wage employees and non-participants. These variables include education, whether the individual is the head of the household, number of children and number of adults aged 15 and higher in the household, and location and region of residence. Next, we obtain predicted probabilities of having a latent wage above the median, given characteristics X_{it}, $\hat{P}_{it} = Pr(I_{it}|X_{it})$, where X_{it} is a vector that includes a Muslim dummy and other characteristics, as outlined above.

In the second step, the predicted probabilities, $\hat{P}_{it}$, that were estimated in the first step are used as sampling weights for the non-participants. That is, in each of the independent imputed samples, wage employees feature with their observed wages, and non-participants feature with a wage above the median with probability $\hat{P}_{it}$ and a wage below the median with probability $1 - \hat{P}_{it}$, conditional on observed characteristics. To implement this approach, we construct 20 independent imputed samples.

[16] Another way to address the selection problem is to model the labour force participation decision explicitly and estimate a structural model of wage offers and participation decision (Heckman 1979). However, the difficulty of exploiting and identifying Heckman selection model in the unconditional quantile regression framework led us to consider this alternative approach.

The final estimates for the statistics of interest are obtained by averaging the estimates across the 20 rounds of imputation. Finally, we estimate and decompose the wage gap between Muslims and Hindus for the imputed sample both at the mean and at the specific quantiles.

It is difficult to predict a priori how correction for selection will affect the results. This effect ultimately depends on the wages that the non-participants earned when they were (later) employed, on the observable characteristics of the non-participants and on estimation methods.

4. Data

We use data from the Labour Force Surveys for 1999-2000 (henceforth LFS 1999), 2005-2006 (henceforth LFS 2005), and 2009 (henceforth LFS 2009) conducted by the Bangladesh Bureau of Statistics (BBS).[17] These three cross-sectional surveys are nationally representative datasets covering the whole of the country disaggregated by urban and rural areas. Different households are surveyed each year in both rural and urban areas across all regions of Bangladesh. The households are selected via stratified random sampling.

The data from the LFS 1999, 2005 and 2009 contain detailed information concerning a range of individual (age, gender, marital status, educational attainment, employment status, hours worked, and wages earned) and household-level characteristics (household size and composition, religion, land holding, location, and asset ownership).

The estimating sample used in this study includes wage employees aged 15–65 years. We choose an upper age limit of 15 to ensure that we do not include child labour. Other observations were excluded if individuals who did not work at all due to illness or disability, those who work without pay, full-time students and self-employed individuals. The main reasons for dropping the self-employed is that the determinants of self-employed earnings are different from those of wages (Ahmed and McGillivray 2015). As such our analysis is not applicable to this group.

[Table 1 about here]

[17] These surveys were respectively published in 2002, 2008 and 2011 and are therefore cited below in the references as BBS (2002; 2008; 2011)

The details of the estimating sample are reported in Table 1. The sample is classified into two groups: Muslims and Hindus. The wage employment (full time and/or part-time) increased in absolute value for both Muslims and Hindus from 1999–2009, but the majority of those who worked for wages were Muslims in both years. The non-participants (i.e., those who did not work at all during the week preceding each survey) are also predominantly Muslims.

The determinants of wages include a set of variables that affect productivity. These variables include inherent ability (unobserved and proxied by the individual's educational attainment), job-related training, male, age group, formal sector, occupation, industry, marital status, number of young children in the household, and location and region of residence.[18]A full list of the variables (and their theoretical justification) included in the wage regression is provided in Table A1 in the Appendix.

[Table 2 about here]

4.1 Descriptive Statistics

Table 2 presents the mean and standard deviation of the variables used in the regression for the wage employees for the 1999, 2005 and 2009 samples, separately for Muslims and Hindus. Relative to Hindus, the Muslim wage employees are younger, and are more likely to be married. However, the wage-earning Muslims come from households with more young children relative to Hindus. These results hold over the period 1999-2009.

Some important changes in the educational qualifications of wage workers (both Muslims and Hindus) were observed over time. Notably, the percentage of Muslims and Hindus with a secondary degree (i.e., those who completed grade 10) increased significantly between 1999 and 2009, although the change for Hindu workers was much higher in 2009. With respect to this category, 22 percent of both Muslims and Hindus completed secondary school, by 2009, this percentage had increased to 43

[18] The contribution of sets of categorical variables (for example, age, education, occupation, industry, region of residence) in explaining the overall *endowment effect* is subject to an identification problem as they are sensitive to the base group used in estimation for such categorical variables. However, we cannot drop this part of analysis as they contribute to the *endowment effect*. Moreover, our expectation is that the extent of this bias is unlikely to impact on our results to such an extent that correcting it would alter our conclusions. To further substantiate our claim, we follow Ahmed and Maitra (*forthcoming*), so that no group is omitted from the wage regression, and instead coefficients on dummy variables are expressed as their deviation from the mean. This way, the sum of the coefficients on a given set of dummy variables always equals zero and there is no identification problem arising because of the choice of the reference group. The results obtained are similar to those presented in the paper.

percent for Muslims and 47 percent for Hindus. On the other hand, the percentage of Muslim wage earners with a graduate degree was significantly lower than the percentage of Hindu wage earners. This result barely changed over time. At the other end of the education spectrum, a higher percentage of Muslim wage earners was with primary education or less, compared with Hindu wage earners.

Further, differences in occupation level exist and exhibit different patterns over time. Notably, the percentage of Muslim and Hindu wage earners in administrative jobs increased considerably from 1999–2009, from 2 percent to 22 per cent for Muslims and from 4 percent to 28 percent for Hindus. This result does not appear to be particularly surprising, as Hindus have experienced greater access to tertiary education. In addition, jobs that require lower educational qualifications and lower skills (e.g., production-related jobs) tend to be dominated by Muslims.

[Table 3 about here]

Table 3 shows the percentage of Muslims and Hindus who worked in the week preceding each survey by educational attainment. There is a reduction in employment rates among Muslims except for those with secondary degree and who are graduates while employment rates increased for Hindus except for those with primary education or less and post-secondary degree between 1999 and 2009. The general decline in employment rates for Muslims reflects their lower levels of educational attainment relative to Hindus during 1999-2009. Note, however, although the employment rates for Muslim and Hindu graduates increased over time, there was a substantial gap in employment rates among highly educated Muslims and Hindus, with the gap increasing in favour of Hindus.

[Table 4 about here]

4.2 Wage Differentials

The earning measure that we use is the (log) of hourly wages. Hourly wages are computed by dividing monthly wages by the total hours of work per month. The survey collected information concerning the usual hours of work per week but not the number of weeks worked during a month. Therefore, the monthly hours of work are computed by multiplying the usual hours of work per week by 52/12. All nominal wages are converted to real values using the National Consumer Price Index, 1999 = 100.

Table 4 shows (log) real hourly wage by educational attainment for Muslim and Hindu workers during 1999-2009. The estimated (log) real hourly wages for both Muslims and Hindus increased

between 1999 and 2009, although the earning advantage was largely greater for Hindus. Looking at the last column, the median (log) wage gaps were -0.059 log points (or -5.7 percent) in 1999 and -0.144 log points (or -13.4 percent) in 2005.[19] By 2009, this gap increased to -0.080 log points (or -7.6 percent). With the exception of 1999, these differences are statistically significant at the 1 percent level. On the other hand, at the mean, the wage gap between Muslim and Hindu employees was 0.013 log points (or 1.3 percent) in 1999, but statistically insignificant; in 2009, this gap decreased to -0.054 log points (or -5.3 percent) and is statistically significant at the 1 percent level, suggesting the reversal of the wage gap between Muslim and Hindu wage earners over time. Looking at the education levels separately, the mean (log) wage gap narrowed substantially for those with primary and highest education groups, reversed for those with secondary and post-secondary education and was unchanged (favouring Hindus) for those with the technical education during the decade 1999-2009. A narrowing and even reversal of the (log) wage gap thus reflects a change in the educational composition of the sample.

[Figure 1 about here]

[Figure 2 about here]

Figure 1 shows average (log) real hourly wage by major industries (i.e., primary, secondary and tertiary) for Muslim and Hindu workers during 1999-2009.[20] In 1999, Muslims earn more than Hindu wage earners in all three industries; by 2009, this is reversed except in the primary industry. This pattern changes slightly when we look at the median (log) real hourly wage by major industries for Muslim and Hindu workers in Figure 2: while among three industries, Hindus earn more than Muslims in the primary industry in 1999, it changed in favour of Muslims in 2009. Although only descriptive, these results indicate that the wage gap between Muslim and Hindu workers is narrowed or even reversed in some industries from 1999 to 2009.

5. Results

5.1 RIF Unconditional Quantile Regression

[19] The percentage term is calculated as $(exp(x) - 1) \times 100)$, where x is 'log-point'.

[20] Primary industry includes agriculture, fishing etc. Secondary industry includes mining and quarrying, manufacturing, electricity and construction. Tertiary industry includes wholesale and retail trade, hospitality, transport, storage and commination services, financial, insurance, real estate and business services, education, community, social and personal services.

The OLS regression estimates for Muslim and Hindu workers for the three survey years are presented in the Appendix Tables A2-A4. Panel A of each table presents estimates for Muslims, and panel B lists these estimates for Hindus, unadjusted for sample selection bias.[21] The notable finding is that men, with few exceptions, earned significantly more than women with both the Muslim and Hindu communities across all the three years of analysis. This echoes the findings of Bhaumik and Chakraborty (2007) for India. Further, the absolute value of the (positive) coefficients of the male dummy variable was lower for the Hindu sample than for the Muslim sample (see also Bhaumik and Chakraborty 2007 for similar findings); however, this wage differential was greater at the lower end of the wage distribution during 1999-2009. We might, therefore, expect that earning disadvantage was greater for *lower-earning* Muslim women. This is very similar to findings reported in previous studies on Bangladesh (see, for example, Ahmed and McGillivray 2015).

Overall, with few exceptions, the returns to education beyond the post-secondary level appear to be modestly higher for Hindu workers; however, this trends had been reversed by 2009. In particular, the returns to the Hindu graduates are higher than for their Muslim counterparts both at the mean and at the lower end of the wage distribution in 1999 and 2005, whereas, in both years, Muslim graduates dominate at the upper end of the distribution. On the other hand, the earning advantage was greater for Hindu workers with technical education, especially at both the lower and the upper ends of the distribution in 2005 and 2009. A similar pattern is not observed in 1999. The job-related training had a positive and a significant effect on wages for Muslim and Hindu workers; however, the earning advantage was greater for Hindu workers across the wage distribution, especially in 2009.

Both Muslim and Hindu workers earned more in the formal sector than their counterparts in the informal sector; however, returns for Muslim workers are higher relative to Hindu workers, especially at the lower end of the distribution. However, the impact of the different levels of occupation on wages of both Muslim and Hindu workers were roughly the same in 1999. The noticeable change observed between 2005 and 2009. For example, Muslim workers, with few exceptions, in professional jobs earned more than does the reference group (i.e., Muslim workers with other occupation) in both 2005

[21] The wage regression results based on the imputed sample are not reported, but these results are available from the author upon request.

and 2009. We find a similar effect for Hindu workers only in 2009; however, the earning advantage was greater for Muslim workers, especially at the upper end of the distribution.

[Table 5 about here]

5.2 Firpo et al. Decomposition

Table 5 presents the decomposition results at the mean and at selected quantiles. The decomposition at the mean reveals that in 1999, the wage difference between Muslim and Hindu workers was 0.013 log points (or 1.3 percent). The decomposition of this gap reveals that this was entirely due to labour market discrimination. After accounting for differences in endowments, the discrimination component was 0.085 log points, which indicates that if Muslims and Hindus obtained wages based on their productive characteristics, Muslims would have earned 8.9 percent higher wages than Hindus. Political discrimination against Hindus by the pro-Islamic BNP party and its allies would have contributed to this findings largely on account of differences in the impact of individual characteristics on earnings. The mean wage gap narrowed in favour of Hindus in 2005 (-0.051 log points or -4.9 percent) as well as in 2009 (-0.054 log points or -5.3 percent). Although smaller in magnitude this results is broadly consistent with findings from a similar study (for example, see Bhaumik and Chakraborty 2007). This advantage is explained by their labour market characteristics over the period 2005-2009. The detailed decomposition in Table 5 shows that the *endowment effect* associated with variables, namely, education and training (in both years) has largely contributed to the wage advantage for Hindus (see also Bhaumik and Chakraborty 2007). Beginning with 2005, Hindu's advantage with educational qualifications is evident from the post-secondary level onwards; by 2009, Hindu workers are largely endowed with graduate degree and technical education (see Table 2). On the other hand, by 2009, the effect of discrimination against Hindus has disappeared completely. Our findings could be related to two important phenomena. First, given the process of economic liberalisation in Bangladesh since 1990s, the labour market are willing to accommodate workers with higher education than those without such education. Second, while new political regime led by the Awami League since 2008 is not necessarily responsible for this change, they may have contributed to the relative rise in earnings of Hindu workers.

The rest of Table 5 decomposes the wage gap between Muslim and Hindu workers at the median, at the bottom and top quantiles. With the exceptions of the 90^{th} quantile in 1999, the wage gap between

Muslims and Hindus narrowed in favour of Hindu workers at selected quantiles over the years. We also find that the relative earnings advantage for Hindus are higher at the lower end of the distribution (-0.097 log points (-9.2 percent) in 1999, -0.182 log points (-16.6 percent) in 2005, and -0.058 log points (-5.6 percent) in 2009 at the 10th quantile) than at the upper end of the distribution (0.068 log points (7 percent) in 1999, -0.036 log points (-3.5 percent) in 2005, and -0.011 log points (- 1.1 percent) in 2009 at the 90th quantile). Interestingly, Levanon and Raviv (2007) found a different result in Israel, where the wage advantage for Jews or Christians compared to Muslims is lower towards the lowest percentiles.

The detailed decomposition reveals that the differences in endowments primarily favoured Hindu workers at both the bottom and upper ends of the wage distribution between1999-2009 that would have contributed significantly to the narrowing of the wage gap in favour of Hindus. The results clearly indicate it is educational qualifications that play the most important role in determining the explained part of the wage gap. Beginning with 1999, Hindu's advantage in educational qualifications is evident at both the bottom and median quantiles; by 2009, Hindu workers favoured substantially, especially at the 10th quantile. The other notable finding is that occupational distribution plays a bigger role for Muslim workers than their educational qualifications, suggesting that it is the sorts of jobs that Muslims end up in–given their qualifications–that are more pertinent to their wage disadvantage than simply their average differences in qualifications (see also Longhi et al. 2009). For example, the differences in occupational distribution while initially in favour of Muslims for lower income quantiles in 1999, they favour Hindus at the 10th and 90th quantiles in 2005, and at the median in 2009.

On the other hand, with the exceptions of 2009, discrimination component had the opposite effects on the wage gap between Muslims and Hindus in the 10th and 90th quantiles. It was actually negative for lower income quantiles, which might tend to reduce the wage gap in favour of Hindus. In addition to less discrimination as a consequence of institutional reform caused by the economic liberalisation,[22] the results might reflect higher returns to schooling for Hindus than for Muslims at the lower end of the wage distribution (see Tables A2 and A3). At the top, while the effect of discrimination is positive due to employer discrimination against the minority group and a 'glass ceiling', the *endowment effect*

[22] A shift to increased reliance on market forces can punish discriminatory wage-setting behaviour and thus reduce the wage gap (Becker 1957).

dominated. Therefore, the net effect at higher income quantiles was a narrowing of the wage gap in favour of Hindus.

Finally, with the exception of a few cases, the magnitude of the approximation errors is generally small and insignificant (the bootstrapped standard errors are computed but not shown). This result indicates that the RIF-based decompositions provided a good approximation of the true wage differentials between Muslim and Hindu workers in our sample. It is important to emphasise that large approximation errors are not uncommon at the mean and at other points of the wage distributions when applying the RIF regression (for example, see Ahmed and Maitra *forthcoming*).

[Table 6 about here]

5.3 Firpo et al. Decomposition on the Imputed Sample

Our discussion so far has referred to unadjusted wage gaps between Muslim and Hindu workers in the sample of employed workers (the base sample). We also decompose the wage gap into the *endowment* and *discrimination* effects for a sample enlarged with wage imputation. We assess the impact of selection into employment on the observed wage gap by comparing the estimates obtained using repeated imputation techniques. The results based on repeated imputation are summarised in Table 6.

In general, the wage gap between Muslims and Hindus for the imputed wage distribution is actually lower than the gap obtained for the base sample during 1999-2009 (Table 5). Therefore, the observed reverse wage gap tends to be overestimated if selection bias effects are ignored in the wage equations. The major factor responsible for the decreased wage gap is that Hindus benefitted from a decline in discrimination over time. It is actually negative at selected quantiles and statistically significant at the 1 percent level. The (unreported) wage regression results suggest that higher returns to education among Hindus than among Muslims are a key driver of this effect. It is also possible that non-participants, especially Hindus, have higher levels of the factors that are expected to be correlated with higher wages (for example, education).

5.4 Robustness and Further Discussion

We have conducted a number of robustness tests on the obtained results, but these are not reported to save space.[23] The following tests were considered, among others: (a) we have computed bootstrapped standard errors for the *endowment effect* and the *discrimination effect*, using 500 replications. The results were very similar to those obtained on the base and imputed samples; (b) we dropped the occupation dummy variables from the analysis, as the choice of occupation is potentially endogenous in the wage equation. The results were very similar to those obtained on the base and imputed samples; (c) one issue that has not been addressed in this paper is that of migration. Thousands of Bangladeshi Hindus were believed to have migrated to neighbouring India to escape communal disturbance since independence in 1971. The outflows of Hindu population to India and other states might have contributed to Hindu wage advantage over time. Evidence presented by Lucas (2005) suggests that emigration led to higher employment for nationals in Bangladesh. How this might impact on the wage gap between Muslims and Hindus, and the selection into employment, for the workers in Bangladesh, however, is unknown. In the absence of any information on the *migration* status of the workers in the data set, there is not much can be done here to address this issue. For the only way (however imperfect) to judge how important migration is to the analysis that is done in this paper, we need to look at a sample of workers who have the least probability of emigration, so that what we observe is *all* individuals and not simply those who did not migrate (Mishra 2007).

Certain districts in Bangladesh can be characterised as *low migration* (LM) and the other as *high migration*. The *high migration* districts tend to be in the centre, east and south-east of the country (about 79 percent of the immigrants hail from these districts); similarly there are LM districts in the south, west and north-west of the country where 21 percent of the immigrants come from these districts (BBS 2012).

The sample that was used in this paper was divided into *high migration* and LM districts. The analysis was done separately for the Muslim and Hindu workers in the LM districts. In 1999 about 33 percent of the wage workers were in LM districts; the equivalent numbers for 2005 was 43 percent and for 2009 was 35 percent. While Hindus have an advantage in terms of mean wages compared to their

[23] They are, however, available from the author upon request.

Muslim counterparts in the LM districts, the wage advantage remained consistently lower than in the nation as a whole, for 1999, 2005 and 2009. As before, their job characteristics explain their wage advantage at the mean, yet the discrimination component is now even smaller in magnitude. We also note that correction for sample selection leads to similar results to those presented in Table 6.

6. Conclusion

Although much research has been performed concerning the gender wage gap in Bangladesh, little information is available concerning wage differences among religious groups. We address this issue using the Bangladesh LFS datasets for 1999, 2005 and 2009. We adopt the unconditional quantile regression model to examine (and decompose) the wage gap between the two main religious groups: Muslims and Hindus across the unconditional wage distribution. We also correct for the selection bias into employment across the unconditional wage distribution using the repeated imputation method.

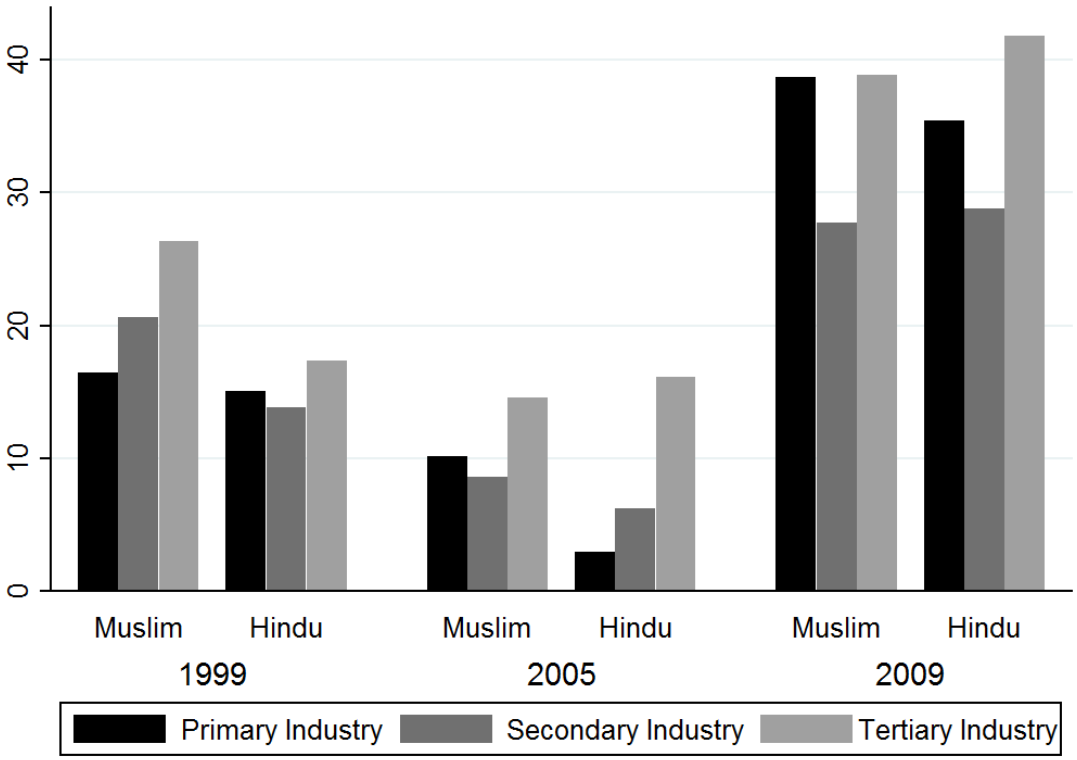
The decomposition results indicate that Hindus fare comparatively well on average in the Bangladesh labour market during 1999-2009, and their wage advantage was greater at the lower end of the wage distribution. The main contributors to this reverse wage gap were improvement in their educational qualifications. The decomposition further indicates that discrimination against Hindus has disappeared completely, especially at the bottom of the distribution; while *high-earning* Hindu workers lost ground due to discrimination over the period 1999-2009. This reveals the fact that although acquisition of human capital and job-related training may be instrumental in giving Hindus competitive wages, Hindus could still be underpaid due to a *taste for discrimination* among employers. However, the difference in productive characteristics narrowed significantly over the years that offset the negative forces and the net effect is a decrease in the wage gap in favour of Hindus.

This paper also demonstrates that imputing wages for workers with no wage observations significantly affects the estimates of the wage gap between Muslims and Hindus across the wage distribution. In particular, the reverse wage gap is likely to be overestimated if the issue of selection into employment is ignored. The major driving force behind this effect was higher returns to education among Hindus than among Muslims. It might be possible that *high-earning* Hindus are less likely to be

employed and therefore imputing wages for *high-educated* Hindus who did not participate could have contributed to convergence in the reverse wage gap.

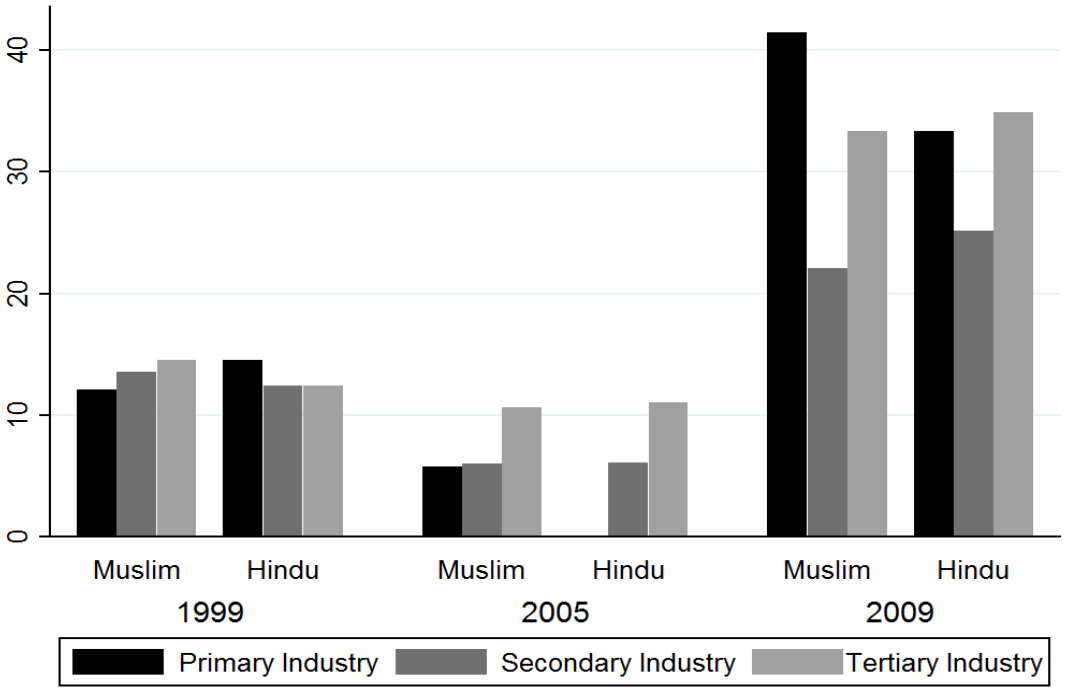
The evidence presented in this paper has significant policy implications. The paper shows that education is a key determinant of the wage gap favours Hindus in Bangladesh. This means that equal access to education and training is imperative in generating greater equality in earnings among religious groups. However, highly educated Hindus still earn considerably less than highly educated Muslims at the top of the distribution, suggesting a glass ceiling for Hindu minorities. This findings reinforce the need for systematic affirmative action scheme on religious grounds in Bangladesh.

Figure 1. Mean wage rates of Muslim and Hindu workers by major industries and year



Notes: The sample includes individuals in the age group of 15-65 years.
Source: Author's calculation from the LFS dataset for various years.

Figure 2. Median wage rates of Muslim and Hindu workers by major industries and year



Notes: The sample includes individuals in the age group of 15-65 years.
Source: Author's calculation from the LFS dataset for various years.

Table 1. Sample selection

	1999		2005		2009	
	Wage employees (%)	Non-participants (%)	Wage employees (%)	Non-participants (%)	Wage employees (%)	Non-participants (%)
Muslim	90.65	91.93	87.66	88.75	87.97	89.42
Hindu	9.65	8.07	12.34	11.25	12.03	10.58
Total	3,496	731	8,807	48,717	9,441	50,069

Notes: The sample includes individuals in the age group of 15-65 years. Non-participants are those who do not work at all during the week preceding each survey.

Source: Author's calculation from the LFS dataset for various years

Table 2. Descriptive statistics for Muslim and Hindu workers by year

	1999				2005				2009			
	Muslim		Hindu		Muslim		Hindu		Muslim		Hindu	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age 15-19	0.119	0.324	0.113	0.317	0.092	0.289	0.056	0.230	0.115	0.319	0.089	0.285
Age 20-24	0.127	0.333	0.138	0.345	0.119	0.324	0.104	0.305	0.154	0.361	0.122	0.328
Age 25-29	0.136	0.343	0.131	0.338	0.144	0.351	0.140	0.347	0.149	0.356	0.138	0.345
Age 30-34	0.141	0.348	0.110	0.313	0.131	0.338	0.136	0.343	0.164	0.370	0.180	0.384
Age 35-39	0.148	0.355	0.110	0.313	0.138	0.345	0.155	0.363	0.104	0.305	0.122	0.328
Age 40-44	0.106	0.308	0.116	0.321	0.122	0.328	0.141	0.348	0.101	0.301	0.118	0.323
Age 45-49	0.100	0.300	0.122	0.328	0.106	0.308	0.104	0.305	0.083	0.277	0.083	0.276
Age 50-54	0.068	0.252	0.113	0.317	0.077	0.266	0.094	0.292	0.074	0.261	0.081	0.273
Age 55-59	0.037	0.188	0.021	0.145	0.045	0.208	0.052	0.223	0.038	0.192	0.048	0.213
Age 60-65*	0.019	0.136	0.024	0.155	0.024	0.153	0.017	0.131	0.018	0.133	0.019	0.138
Male	0.718	0.450	0.682	0.466	0.824	0.380	0.772	0.420	0.834	0.372	0.776	0.417
less than a primary education*	0.249	0.432	0.208	0.406	0.113	0.317	0.076	0.266	0.144	0.351	0.098	0.297
Primary education completed	0.192	0.394	0.153	0.360	0.160	0.366	0.127	0.333	0.157	0.363	0.123	0.329
Secondary education completed	0.220	0.414	0.217	0.413	0.366	0.482	0.321	0.467	0.432	0.495	0.467	0.499
Post-secondary education completed	0.181	0.385	0.239	0.427	0.134	0.340	0.171	0.377	0.098	0.297	0.092	0.290
Graduate	0.152	0.359	0.177	0.383	0.221	0.415	0.296	0.457	0.165	0.371	0.210	0.407
Technical	0.006	0.077	0.006	0.078	0.006	0.077	0.008	0.091	0.005	0.073	0.010	0.098
Job- related training	0.036	0.187	0.012	0.110	0.106	0.307	0.166	0.372	0.107	0.309	0.124	0.330
Married	0.714	0.452	0.670	0.471	0.745	0.436	0.730	0.444	0.726	0.446	0.707	0.455
No. of children, aged 0-5 in the household	0.404	0.679	0.278	0.580	0.308	0.567	0.246	0.505	0.333	0.605	0.279	0.557
No. of children, aged 6-14 in the household	0.759	1.069	0.618	0.968	0.646	0.946	0.530	0.845	0.535	0.874	0.474	0.776
Formal sector	0.785	0.411	0.823	0.383	0.777	0.416	0.734	0.442	0.541	0.498	0.474	0.500
Professional	0.037	0.189	0.012	0.110	0.269	0.443	0.344	0.475	0.021	0.142	0.015	0.121
Administrative	0.027	0.163	0.043	0.203	0.010	0.099	0.014	0.117	0.221	0.415	0.289	0.453
Clerical	0.109	0.311	0.125	0.332	0.133	0.340	0.142	0.349	0.090	0.287	0.088	0.283
Service	0.003	0.059	0.001	0.000	0.117	0.321	0.081	0.273	0.050	0.217	0.028	0.166
Sales	0.045	0.208	0.058	0.234	0.114	0.318	0.141	0.348	0.095	0.294	0.136	0.342
Agricultural labourer	0.351	0.477	0.291	0.455	0.017	0.131	0.037	0.188	0.093	0.291	0.100	0.301
Production labourer	0.056	0.231	0.049	0.216	0.314	0.464	0.189	0.391	0.364	0.481	0.288	0.453
Other*	0.069	0.253	0.089	0.285	0.025	0.157	0.053	0.225	0.065	0.247	0.056	0.231
Primary industry*	0.344	0.475	0.284	0.452	0.015	0.121	0.037	0.188	0.098	0.297	0.101	0.302
Secondary industry	0.066	0.248	0.064	0.246	0.004	0.061	0.004	0.061	0.337	0.473	0.319	0.466
Tertiary industry	0.288	0.453	0.318	0.466	0.543	0.498	0.436	0.496	0.565	0.496	0.580	0.494
Urban	0.785	0.411	0.670	0.471	0.636	0.481	0.656	0.475	0.427	0.495	0.443	0.497
Dhaka*	0.501	0.500	0.343	0.475	0.356	0.479	0.273	0.446	0.364	0.481	0.234	0.424
Barisal	0.042	0.201	0.070	0.256	0.088	0.283	0.080	0.271	0.103	0.304	0.087	0.282
Chittagong	0.159	0.366	0.138	0.345	0.172	0.378	0.234	0.423	0.206	0.405	0.226	0.419
Khulna	0.151	0.358	0.232	0.423	0.143	0.350	0.132	0.338	0.112	0.315	0.126	0.332
Rajshahi	0.135	0.342	0.113	0.317	0.209	0.407	0.159	0.366	0.154	0.361	0.069	0.253
Sylhet	0.011	0.105	0.104	0.306	0.031	0.175	0.122	0.328	0.061	0.240	0.258	0.438
N	3,169		327		7,720		1,087		8,305		1,136	

Notes: *implies reference categories in the estimated equations.
Source: Author's calculation from the LFS dataset for various years.

Table 3. Employment rates of Muslim and Hindu workers by education and year

	Less than Primary (%)	Primary (%)	Secondary (%)	Post-Secondary (%)	Graduate (%)	Technical (%)
1999						
Muslim	24.87	19.25	21.99	18.08	15.21	0.6
Hindu	20.8	15.29	21.71	23.85	17.74	0.61
2005						
Muslim	11.32	15.98	36.65	13.37	22.09	0.6
Hindu	7.64	12.7	32.11	17.11	29.62	0.83
2009						
Muslim	14.35	15.67	43.15	9.77	16.53	0.53
Hindu	9.77	12.32	46.74	9.24	20.95	0.97

Notes: The sample includes individuals in the age group of 15-65 years.
Source: Author's calculation from the LFS dataset for various years.

Table 4. Wage rates of Muslim and Hindu workers by education and year

	Less than Primary	Primary	Secondary	Post-Secondary	Graduate	Technical	All levels	All levels
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Median
1999								
Muslim	1.844	2.259	2.457	2.809	3.280	3.480	2.461	2.515
	(0.750)	(0.677)	(0.614)	(0.732)	(0.700)	(1.068)	(0.848)	(0.696)
Hindu	1.805	2.095	2.307	2.824	3.109	4.422	2.448	2.574
	(0.686)	(0.656)	(0.642)	(0.533)	(0.536)	(0.172)	(0.782)	(0.820)
	0.039	***0.164***	***0.150***	***-0.015***	***0.171***	***-0.942***	***0.013***	***-0.059***
2005								
Muslim	1.773	2.071	2.381	2.872	3.184	3.057	2.509	2.675
	(0.991)	(0.907)	(0.970)	(0.822)	(0.888)	(1.154)	(1.037)	(0.623)
Hindu	1.933	1.718	2.295	2.845	3.176	3.650	2.560	2.819
	(0.893)	(1.122)	(0.942)	(0.850)	(0.729)	(0.333)	(1.031)	(0.639)
	-0.160	***0.353***	***0.086***	***0.027***	***0.008***	***-0.593***	***-0.051***	***-0.144****
2009								
Muslim	3.180	3.078	3.306	3.545	3.843	3.766	3.366	3.467
	(0.619)	(0.607)	(0.595)	(0.552)	(0.616)	(0.474)	(0.648)	(0.406)
Hindu	3.242	3.069	3.309	3.632	3.839	4.070	3.420	3.547
	(0.551)	(0.581)	(0.587)	(0.590)	(0.608)	(0.820)	(0.645)	(0.347)
	-0.062	***0.009***	***-0.003***	***-0.087***	***0.004***	***-0.304***	***-0.054****	***-0.080****

Notes: The sample includes individuals in the age group of 15-65 years. Wage rates are in 1999 Taka. Standard deviations in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Author's calculation from the LFS dataset for various years.

Table 5. Firpo et al. decomposition of the wage gap between Muslim and Hindu workers by year

	1999				2005				2009			
	Mean	0.10	0.50	0.90	Mean	0.10	0.50	0.90	Mean	0.10	0.50	0.90
Total wage gap	**0.013**	**-0.097**	**-0.059**	**0.068**	**-0.051**	**-0.182**	**-0.144**	**-0.036**	**-0.054**	**-0.058**	**-0.080**	**-0.011**
	(0.012)	(0.027)	(0.043)	(0.036)	(0.020)	(0.088)	(0.020)	(0.018)	(0.011)	(0.012)	(0.011)	(0.009)
Endowment effects attributable to[a]												
Education	*-0.083*	*-0.090*	*-0.091*	*0.055*	*-0.076*	*-0.158*	*-0.055*	*-0.012*	*0.003*	*-0.078*	*0.068*	*0.018*
Training	*0.005*	*0.004*	*0.005*	*0.015*	*-0.009*	*-0.014*	*-0.010*	*-0.002*	*-0.003*	*-0.004*	*-0.002*	*-0.006*
Occupation	*0.045*	*0.075*	*0.059*	*-0.013*	*0.033*	*-0.769*	*0.028*	*-0.049*	*0.024*	*0.034*	*-0.036*	*0.015*
Endowment effects	-0.030	0.005	-0.031	0.013	-0.111	-0.094	-0.164	-0.105	-0.025	-0.037	-0.053	0.002
Approximation errors	-0.042	-0.003	-0.065	-0.070	0.038	-0.062	0.065	0.058	-0.027	-0.043	-0.016	-0.024
Subtotal 1	**-0.072**	**0.002**	**-0.096**	**-0.057**	**-0.073**	**-0.156**	**-0.099**	**-0.047**	**-0.052**	**-0.080**	**-0.069**	**-0.022**
	(0.008)	(0.006)	(0.014)	(0.009)	(0.003)	(0.011)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Discrimination effects	0.043	-0.098	-0.030	0.056	0.059	-0.089	0.020	0.068	-0.030	-0.027	-0.028	-0.014
Approximation errors	0.042	-0.001	0.067	0.069	-0.037	0.063	-0.065	-0.057	0.028	0.049	0.017	0.024
Subtotal 2	**0.085**	**-0.099**	**0.037**	**0.125**	**0.022**	**-0.026**	**-0.045**	**0.011**	**-0.002**	**0.022**	**-0.011**	**0.010**
	(0.032)	(0.025)	(0.035)	(0.040)	(0.018)	(0.060)	(0.021)	(0.012)	(0.007)	(0.012)	(0.009)	(0.009)

Notes: Wage rates for Muslims are the reference category in the decomposition. A positive entry indicates an advantage in favour of Muslim workers.

All decomposition results reported are rounded to three digits after the decimal. Subtotals 1 and 2 are computed as $\left[\left(\bar{X}_{mt}\hat{\beta}_{mt}(\tau) - \bar{X}_{ht}\hat{\beta}_{ct}(\tau)\right) + \hat{R}_E(\tau)\right]$ $\left[\bar{X'}_{ht}\left(\hat{\beta}_{ct}(\tau) - \hat{\beta}_{ht}(\tau)\right) + \hat{R}_C(\tau)\right]$.

[a] The following explanatory variables are contributed to the endowment effect: age, education, male, number of children in the household, job-related training, formal sector, occupation, industry, and location and region of residence. The results for age, marital status, male, number of children in the household, formal sector, industry, and location and region of residence are suppressed for the sake of brevity.

Standard errors are in parentheses and are estimated based on 200 bootstrap replications.

Source: Author's calculation from the LFS dataset for various years.

Table 6. Firpo et al. decomposition of the wage gap between Muslim and Hindu workers by year using the imputed sample

	1999				2005				2009			
	Mean	0.10	0.50	0.90	Mean	0.10	0.50	0.90	Mean	0.10	0.50	0.90
Total wage gap	**-0.006**	**-0.105**	**-0.076**	**0.031**	**-0.061**	**-0.051**	**-0.059**	**-0.067**	**-0.047**	**-0.070**	**-0.080**	**-0.031**
	(0.032)	(0.021)	(0.044)	(0.036)	(0.006)	(0.011)	(0.005)	(0.007)	(0.002)	(0.002)	(0.003)	(0.002)
Endowment effects attributable to[a]												
Education	*-0.023*	*0.037*	*-0.135*	*0.064*	*0.048*	*-0.052*	*0.029*	*0.271*	*-0.028*	*-0.170*	*0.033*	*-0.019*
Training	*0.003*	*0.002*	*0.003*	*0.010*	*-0.002*	*-0.001*	*-0.004*	*0.002*	*-0.001*	*-0.001*	*-0.001*	*-0.002*
Occupation	*-0.001*	*-0.024*	*0.010*	*-0.024*	*-0.047*	*-0.132*	*-0.043*	*-0.028*	*-0.003*	*-0.001*	*-0.008*	*-0.004*
Endowment effects	-0.006	0.086	-0.024	-0.032	0.256	0.758	0.156	0.067	0.044	0.013	0.169	0.085
Approximation errors	0.058	0.024	0.060	0.048	0.083	0.090	0.084	0.066	0.020	0.021	0.025	-0.013
Subtotal 1	**0.052**	**0.110**	**0.036**	**0.016**	**0.339**	**0.848**	**0.240**	**0.133**	**0.064**	**0.034**	**0.194**	**0.072**
	(0.001)	(0.003)	(0.001)	(0.003)	(0.007)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Discrimination effects	0.001	-0.192	-0.053	0.065	-0.316	-0.808	-0.215	-0.134	-0.091	-0.083	-0.249	-0.116
Approximation errors	-0.059	-0.023	-0.060	-0.049	-0.083	-0.091	-0.084	-0.066	-0.020	-0.021	-0.025	0.013
Subtotal 2	**-0.058**	**-0.215**	**-0.113**	**0.014**	**-0.399**	**-0.899**	**-0.299**	**-0.200**	**-0.111**	**-0.104**	**-0.274**	**-0.103**
	(0.031)	(0.023)	(0.039)	(0.035)	(0.006)	(0.012)	(0.006)	(0.006)	(0.002)	(0.002)	(0.003)	(0.003)

Notes: Wage rates for Muslims are the reference category in the decomposition. A positive entry indicates an advantage in favour of Muslim workers.

All decomposition results reported are rounded to three digits after the decimal. Subtotals 1 and 2 are computed as $\left[\left(\bar{X}_{mt}\hat{\beta}_{mt}(\tau) - \bar{X}_{ht}\hat{\beta}_{ct}(\tau)\right) + \hat{R}_E(\tau)\right]$ $\left[\bar{X}'_{ht}\left(\hat{\beta}_{ct}(\tau) - \hat{\beta}_{ht}(\tau)\right) + \hat{R}_C(\tau)\right]$.

[a] The following explanatory variables are contributed to the endowment effect: age, education, male, number of children in the household, job-related training, formal sector, occupation, industry, and location and region of residence. The results for age, marital status, male, number of children in the household, formal sector, industry, and location and region of residence are suppressed for the sake of brevity.

Standard errors are in parentheses and are estimated based on 200 bootstrap replications.

Source: Author's calculation from the LFS dataset for various years.

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Appendix

Table A1. Definition of Variables

Variables	Definition of variables
Age	
Age 15-19	1 if age is between 15 and 19 years
Age 20-24	1 if age is between 20 and 24 years
Age 25-29	1 if age is between 25 and 29 years
Age 30-34	1 if age is between 30 and 34 years
Age 35-39	1 if age is between 35 and 39 years
Age 40-44	1 if age is between 40 and 44 years
Age 45-49	1 if age is between 45 and 49 years
Age 50-54	1 if age is between 50 and 54 years
Age 55-59	1 if age is between 55 and 59 years
Age 60-65	1 if age is between 60 and 65 years
Education[a]	
less than a primary education	1 if individual has less than a primary education
Primary education completed	1 if individual completed Grade 5
Secondary education completed	1 if individual completed Grade 10/SSC[b]
Post-secondary education completed	1 if individual completed Grade 12/HSC[c]
Graduate	1 if individual attains at least a Bachelor's degree
Technical	1 if individual attains technical education[d]
Job-related training	1 if individual has job-related training
Married	1 if individual is married
Male	1 if individual is a male
No. of children[e]	
No. of children, aged 0-5 in the household	No. of children between 0 and 5 years in the household
No. of children, aged 6-14 in the household	No. of children between 6 and 14 years in the household
No. of adults, aged 15 and higher in the household	No. of other adults aged, 15 years or higher in the household
Head of the household	1 if individual is the head of the household
Formal sector	1 if individual works in formal sector
Occupation[f]	
Professional	1 if occupation category is professional
Administrative	1 if occupation category is administrative
Clerical	1 if occupation category is clerical
Service	1 if occupation category is service
Sales	1 if occupation category is sales
Agricultural labourer	1 if occupation category is agricultural
Production labourer	1 if occupation category is production
Other	1 if occupation category is others
Industry	
Primary industry	1 if industry category is primary
Secondary industry	1 if industry category is secondary
Tertiary industry	1 if industry category is tertiary

(Continued)

Table A1. (Continued)

Variables	Definition of variables
Urban	1 if individual lives in urban areas
Region[g]	
Barisal	1 if individual lives in Barisal
Chittagong	1 if individual lives in Chittagong
Dhaka	1 if individual lives in Dhaka
Khulna	1 if individual lives in Khulna
Rajshahi	1 if individual lives in Rajshahi
Sylhet	1 if individual lives in Sylhet

Notes: [a] The theory of human capital argues that personal earnings are a positive function of educational attainment. We use five dummies to capture the highest level of educational attainment of the individual: primary education completed (Grade 5), secondary education completed (Grade 10/Secondary School Certificate), post-secondary education completed (Grade 12/Higher Secondary School Certificate), graduate (at least completed a Bachelor's degree) and Technical education. The reference category includes those individuals with less than a primary education.

[b] SSC = Secondary School certificate. [c] HSC = Higher-Secondary School certificate. [d] Technical = It has been organised in three tiers: degree level education in engineering and technology, technician level education, and trade level training.

[e] It is often argued that the number of children in the household might capture any wage penalty that is associated with having children, due to both the reduced labour supply and the reduced commitment to the labour market, which reduces productivity.

[f] We include six occupational category dummies: professional, administrative, clerical, service, sales, agriculture and production. The reference category is 'others'. One could argue that occupation variables should not be included as explanatory variables in the wage regression because of the possibility that occupation is endogenous. An additional reason for omitting these variables is that employers' discriminatory practices could be highly correlated with occupation. On the other hand, it is believed that these occupational controls might embody unmeasured occupation-specific human capital. Therefore, we might overlook the potential effect of unobserved human capital if we exclude such controls from the analysis. Arulampalam et al. (2007) argue that estimates with these controls can be viewed as a lower bound of the extent of discrimination.

[g] The region dummy variables control for spatial variation in prices, which are likely to be significant, with higher wages and prices in Dhaka (the capital for Bangladesh) than in other regions. The region dummy variables also control for region-specific differences in labour markets (such as unemployment rates), which might affect wages. Similarly, the regional dummies will control for the potential measurement issue that the quality and availability of education facilities differ markedly across regions, which may result in different levels of human capital accumulation in different regions. For example, programs such as the Food for Education, Primary School Stipend Program, Female Secondary School Assessment Project, and School Feeding Program were implemented in many regions to improve basic education outcomes. Regional dummies control for the effect of such programs.

Table A2. OLS and unconditional quantile regression estimates of Muslim and Hindu workers
LFS 1999

	Panel A: Muslim				**Panel B: Hindu**			
	OLS	0.10	0.50	0.90	OLS	0.10	0.50	0.90
Age 15-19	-0.283***	-0.172	-0.398***	-0.121	-0.291	0.279	-0.930***	-0.116
	(0.090)	(0.221)	(0.129)	(0.175)	(0.218)	(0.482)	(0.321)	(0.303)
Age 20-24	-0.172**	0.208	-0.281**	-0.200	-0.078	0.515	-0.456	-0.108
	(0.087)	(0.202)	(0.129)	(0.175)	(0.218)	(0.460)	(0.338)	(0.301)
Age 25-29	-0.198**	-0.118	-0.199	-0.246	-0.117	0.282	-0.375	-0.149
	(0.086)	(0.200)	(0.127)	(0.177)	(0.225)	(0.459)	(0.326)	(0.318)
Age 30-34	-0.004	0.127	0.041	-0.169	0.072	0.502	-0.315	-0.216
	(0.086)	(0.191)	(0.128)	(0.178)	(0.221)	(0.440)	(0.348)	(0.317)
Age 35-39	0.024	-0.018	0.117	-0.085	-0.137	0.078	-0.142	-0.312
	(0.088)	(0.192)	(0.128)	(0.181)	(0.226)	(0.457)	(0.328)	(0.331)
Age 40-44	0.103	-0.040	0.245*	-0.030	-0.053	0.290	-0.235	-0.168
	(0.087)	(0.191)	(0.129)	(0.186)	(0.225)	(0.451)	(0.334)	(0.347)
Age 45-49	0.158*	-0.049	0.295**	0.228	0.167	0.309	-0.003	0.437
	(0.088)	(0.191)	(0.130)	(0.192)	(0.227)	(0.440)	(0.325)	(0.369)
Age 50-54	0.186**	0.013	0.175	0.488**	-0.131	0.181	-0.420	-0.015
	(0.093)	(0.192)	(0.134)	(0.205)	(0.243)	(0.452)	(0.342)	(0.377)
Age 55-59	0.302***	-0.007	0.352**	0.685***	0.503**	0.457	0.109	-0.031
	(0.101)	(0.203)	(0.137)	(0.242)	(0.253)	(0.462)	(0.415)	(0.506)
Male	0.365***	0.492***	0.434***	0.071	0.326***	0.296**	0.370***	0.340***
	(0.030)	(0.067)	(0.040)	(0.046)	(0.075)	(0.121)	(0.126)	(0.095)
Primary education completed	0.207***	0.334***	0.221***	-0.000	0.190*	0.208	0.349**	-0.227*
	(0.035)	(0.081)	(0.052)	(0.041)	(0.105)	(0.224)	(0.173)	(0.122)
Secondary education completed	0.344***	0.357***	0.487***	0.003	0.282***	0.238	0.313*	-0.358***
	(0.035)	(0.075)	(0.053)	(0.045)	(0.104)	(0.195)	(0.171)	(0.120)
Post-secondary education completed	0.615***	0.331***	0.870***	0.376***	0.751***	0.583***	1.058***	0.083
	(0.040)	(0.078)	(0.053)	(0.069)	(0.095)	(0.168)	(0.165)	(0.141)
Graduate	0.992***	0.374***	1.107***	1.699***	1.001***	0.540***	1.285***	0.631***
	(0.043)	(0.073)	(0.053)	(0.109)	(0.110)	(0.159)	(0.171)	(0.210)
Technical	1.090***	0.127	0.930***	2.714***	1.748***	0.334	0.816*	2.008***
	(0.188)	(0.186)	(0.177)	(0.499)	(0.166)	(0.230)	(0.420)	(0.417)
Job-related training	0.209***	0.186***	0.208***	0.613***	0.773***	0.235	1.376***	0.463
	(0.045)	(0.047)	(0.078)	(0.164)	(0.226)	(0.275)	(0.484)	(0.631)
Married	0.137***	0.227***	0.134***	0.068	0.157*	0.050	0.121	0.259**
	(0.033)	(0.078)	(0.046)	(0.060)	(0.089)	(0.170)	(0.140)	(0.103)
Formal sector	0.337***	0.775***	0.219***	0.070*	0.370***	0.559***	0.430***	0.097
	(0.031)	(0.079)	(0.043)	(0.041)	(0.093)	(0.172)	(0.146)	(0.093)
Professional	-0.003	0.098	0.022	0.070	0.245	0.207	0.347	0.008
	(0.062)	(0.096)	(0.087)	(0.165)	(0.167)	(0.295)	(0.468)	(0.418)
Administrative	0.035	0.010	-0.061	0.101	-0.014	0.028	0.087	0.472
	(0.112)	(0.141)	(0.106)	(0.195)	(0.128)	(0.178)	(0.252)	(0.391)
Clerical	-0.059	-0.001	-0.064	-0.109	-0.236**	-0.271	-0.356	-0.108
	(0.049)	(0.084)	(0.068)	(0.110)	(0.118)	(0.169)	(0.221)	(0.262)
Service	0.070	0.133	-0.039	-0.081	0.000	0.000	0.000	0.000
	(0.189)	(0.112)	(0.319)	(0.473)	(0.000)	(0.000)	(0.000)	(0.000)
Sales	-0.101*	0.182	-0.248***	-0.101	-0.360***	-0.373	-0.555**	-0.158
	(0.060)	(0.117)	(0.089)	(0.124)	(0.134)	(0.230)	(0.241)	(0.306)
Agricultural labourer	0.034	0.079	0.045	-0.008	0.036	0.092	-0.014	-0.214*
	(0.026)	(0.061)	(0.038)	(0.051)	(0.082)	(0.122)	(0.145)	(0.110)

Table A2. (Continued)

	Panel A: Muslim				**Panel B: Hindu**			
	OLS	0.10	0.50	0.90	OLS	0.10	0.50	0.90
Production labourer	0.095	-0.021	0.029	0.161	0.105	0.204	0.017	0.509
	(0.065)	(0.119)	(0.087)	(0.140)	(0.155)	(0.211)	(0.285)	(0.365)
Secondary industry	-0.000	0.138	0.045	-0.146	-0.121	0.049	-0.267	-0.538**
	(0.054)	(0.105)	(0.086)	(0.113)	(0.152)	(0.236)	(0.294)	(0.245)
Tertiary industry	0.096**	0.053	0.121**	0.079	0.189*	0.233	0.085	0.290
	(0.041)	(0.078)	(0.056)	(0.085)	(0.101)	(0.145)	(0.212)	(0.220)
Urban	0.120***	0.015	0.095**	0.196***	0.121	0.027	0.039	0.360***
	(0.026)	(0.059)	(0.041)	(0.048)	(0.076)	(0.113)	(0.131)	(0.115)
Constant	1.341***	-0.068	1.311***	2.884***	1.268***	0.085	1.584***	2.787***
	(0.092)	(0.231)	(0.128)	(0.180)	(0.228)	(0.502)	(0.340)	(0.326)
Observations	3,169	3,169	3,169	3,169	327	327	327	327
R^2	0.498	0.185	0.405	0.277	0.624	0.216	0.509	0.390

Notes: Robust standard errors are in parentheses. The result is rounded to three digits after the decimal. Included in the regression specification but not reported are number of children and dummy variables for region of residence. The results for counterfactual wage regression estimates $\hat{\beta}_{ct}$ are not reported. However, counterfactual wage distributions assume that men's returns to labour market characteristics apply for women, and therefore $\hat{\beta}_{ct}$ is comparable to $\hat{\beta}_{mt}$. A similar argument may apply the wage gap between Muslims and Hindus.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Author's calculation from the LFS dataset for 1999.

Table A3. OLS and unconditional quantile regression estimates of Muslim and Hindu workers LFS 2005

	Panel A: Muslim				**Panel B: Hindu**			
	OLS	0.10	0.50	0.90	OLS	0.10	0.50	0.90
Age 15-19	-0.300***	0.483	-0.529***	-0.071	-0.687***	-4.213***	-0.446*	0.146
	(0.079)	(0.772)	(0.074)	(0.094)	(0.173)	(1.102)	(0.245)	(0.199)
Age 20-24	-0.230***	0.433	-0.458***	-0.205**	-0.569***	-2.624***	-0.448*	-0.033
	(0.074)	(0.705)	(0.072)	(0.093)	(0.146)	(0.798)	(0.242)	(0.174)
Age 25-29	-0.149**	0.685	-0.273***	-0.342***	-0.504***	-2.519***	-0.350	-0.058
	(0.070)	(0.653)	(0.069)	(0.093)	(0.138)	(0.696)	(0.237)	(0.175)
Age 30-34	-0.085	0.104	-0.120*	-0.240**	-0.300**	-1.326***	-0.133	-0.151
	(0.071)	(0.656)	(0.069)	(0.096)	(0.123)	(0.488)	(0.234)	(0.171)
Age 35-39	0.049	0.589	0.016	-0.104	-0.330***	-1.636***	-0.166	-0.051
	(0.070)	(0.646)	(0.069)	(0.097)	(0.124)	(0.523)	(0.231)	(0.178)
Age 40-44	0.111	0.835	0.081	0.033	-0.255**	-1.677***	-0.043	-0.029
	(0.071)	(0.651)	(0.069)	(0.100)	(0.129)	(0.596)	(0.232)	(0.183)
Age 45-49	0.163**	0.568	0.131*	0.188*	-0.090	-1.112**	0.022	0.262
	(0.072)	(0.648)	(0.069)	(0.103)	(0.122)	(0.474)	(0.233)	(0.195)
Age 50-54	0.227***	1.446**	0.122*	0.227**	-0.118	-1.892***	0.104	0.328
	(0.071)	(0.637)	(0.070)	(0.107)	(0.134)	(0.608)	(0.234)	(0.205)
Age 55-59	0.225***	0.922	0.146*	0.172	-0.007	-0.642	0.187	0.203
	(0.077)	(0.676)	(0.075)	(0.119)	(0.131)	(0.520)	(0.243)	(0.220)
Male	0.192***	0.247	0.209***	0.086***	0.025	-0.233	0.023	0.040
	(0.028)	(0.260)	(0.025)	(0.032)	(0.064)	(0.382)	(0.064)	(0.078)
Primary education completed	0.303***	2.225***	0.144***	0.009	0.216*	1.333	0.071	0.034
	(0.042)	(0.444)	(0.035)	(0.022)	(0.122)	(0.947)	(0.098)	(0.055)
Secondary education completed	0.459***	2.384***	0.420***	0.082***	0.471***	2.128**	0.353***	0.125**
	(0.039)	(0.411)	(0.033)	(0.025)	(0.114)	(0.919)	(0.092)	(0.061)
Post-secondary education completed	0.720***	3.279***	0.716***	0.229***	0.737***	2.455**	0.708***	0.357***
	(0.045)	(0.438)	(0.042)	(0.049)	(0.129)	(0.981)	(0.118)	(0.108)
Graduate	0.964***	3.276***	0.878***	0.973***	1.057***	3.071***	1.024***	0.837***
	(0.046)	(0.437)	(0.041)	(0.056)	(0.128)	(0.975)	(0.113)	(0.122)
Technical	0.931***	2.521**	0.958***	0.974***	1.524***	3.502***	1.480***	1.408**
	(0.149)	(1.092)	(0.121)	(0.255)	(0.160)	(1.001)	(0.127)	(0.581)
Job-related training	0.191***	0.502**	0.192***	0.200***	-0.001	-0.372	0.071	0.222*
	(0.030)	(0.205)	(0.030)	(0.059)	(0.072)	(0.389)	(0.072)	(0.124)
Married	0.128***	0.789**	0.047	0.109***	0.000	-0.447	-0.041	-0.003
	(0.032)	(0.308)	(0.031)	(0.032)	(0.082)	(0.518)	(0.080)	(0.082)
Formal sector	0.399***	2.188***	0.367***	0.107***	0.250***	0.075	0.265***	0.127**
	(0.028)	(0.275)	(0.025)	(0.022)	(0.065)	(0.447)	(0.066)	(0.059)
Professional	0.199***	-0.260	0.231***	0.090	-0.175	-1.588**	-0.047	-0.027
	(0.064)	(0.656)	(0.065)	(0.058)	(0.129)	(0.761)	(0.159)	(0.123)
Administrative	0.398***	0.265	0.400***	0.395**	-0.261	-2.077	-0.161	-0.296
	(0.108)	(0.937)	(0.111)	(0.189)	(0.202)	(1.435)	(0.245)	(0.239)
Clerical	0.369***	-0.035	0.325***	0.523***	-0.050	-1.534*	0.094	0.363**
	(0.066)	(0.664)	(0.067)	(0.071)	(0.133)	(0.784)	(0.165)	(0.143)
Service	0.123*	-0.339	0.158**	0.023	-0.259*	-1.574*	-0.289*	0.246*
	(0.065)	(0.683)	(0.065)	(0.051)	(0.154)	(0.948)	(0.166)	(0.136)
Sales	0.195***	0.719	0.191***	-0.009	-0.360***	-2.025***	-0.252	0.018
	(0.065)	(0.678)	(0.066)	(0.052)	(0.127)	(0.759)	(0.164)	(0.115)
Agricultural labourer	-0.327***	-5.898***	-0.064	0.255***	-2.048***	-14.147***	-0.703***	-0.037
	(0.120)	(1.230)	(0.093)	(0.096)	(0.227)	(1.552)	(0.203)	(0.149)

Table A3. (Continued)

	Panel A: Muslim				**Panel B: Hindu**			
	OLS	0.10	0.50	0.90	OLS	0.10	0.50	0.90
Production labourer	0.089	-0.446	0.075	-0.032	-0.356***	-1.835**	-0.312*	-0.079
	(0.063)	(0.662)	(0.062)	(0.050)	(0.130)	(0.787)	(0.161)	(0.108)
Secondary industry	0.046	2.523	-0.168	0.178	0.605	9.465***	-0.487**	0.051
	(0.164)	(1.701)	(0.132)	(0.145)	(0.501)	(2.955)	(0.196)	(0.116)
Tertiary industry	-0.048**	-0.507**	-0.111***	0.146***	0.043	0.386	-0.080	0.210**
	(0.024)	(0.200)	(0.024)	(0.036)	(0.062)	(0.366)	(0.064)	(0.095)
Urban	0.202***	0.762***	0.141***	0.269***	0.215***	0.614	0.135**	0.250***
	(0.022)	(0.197)	(0.021)	(0.022)	(0.059)	(0.401)	(0.056)	(0.058)
Constant	1.226***	-3.915***	1.582***	2.936***	2.230***	2.882***	2.330***	2.919***
	(0.095)	(0.994)	(0.091)	(0.109)	(0.184)	(0.988)	(0.275)	(0.215)
Observations	7,720	7,720	7,720	7,720	1,087	1,087	1,087	1,087
R^2	0.329	0.075	0.371	0.231	0.455	0.284	0.425	0.218

Notes: Robust standard errors are in parentheses. The result is rounded to three digits after the decimal. Included in the regression specification but not reported are number of children and dummy variables for region of residence. The results for counterfactual wage regression estimates $\hat{\beta}_{ct}$ are not reported. However, counterfactual wage distributions assume that men's returns to labour market characteristics apply for women, and therefore $\hat{\beta}_{ct}$ is comparable to $\hat{\beta}_{mt}$. A similar argument may apply the wage gap between Muslims and Hindus.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Author's calculation from the LFS dataset for 2005.

Table A4. OLS and unconditional quantile regression estimates of Muslim and Hindu workers, LFS 2009

	Panel A: Muslim				**Panel B: Hindu**			
	OLS	0.10	0.50	0.90	OLS	0.10	0.50	0.90
Age 15-19	-0.184***	-0.357***	-0.155**	-0.037	-0.143	-0.440	-0.021	0.014
	(0.050)	(0.103)	(0.074)	(0.077)	(0.125)	(0.294)	(0.134)	(0.165)
Age 20-24	-0.111**	-0.071	-0.126*	-0.026	-0.105	-0.209	-0.098	0.066
	(0.047)	(0.094)	(0.071)	(0.076)	(0.117)	(0.263)	(0.130)	(0.169)
Age 25-29	-0.000	0.077	0.004	0.010	0.088	0.047	0.043	0.143
	(0.046)	(0.090)	(0.070)	(0.075)	(0.114)	(0.243)	(0.126)	(0.170)
Age 30-34	0.059	0.144	0.067	0.077	0.008	0.076	-0.030	-0.038
	(0.046)	(0.088)	(0.069)	(0.077)	(0.107)	(0.231)	(0.123)	(0.166)
Age 35-39	0.088*	0.163*	0.119*	0.072	-0.004	-0.060	0.041	-0.001
	(0.047)	(0.089)	(0.071)	(0.080)	(0.110)	(0.240)	(0.125)	(0.171)
Age 40-44	0.112**	0.152*	0.116	0.263***	0.107	0.067	0.088	0.078
	(0.047)	(0.088)	(0.071)	(0.083)	(0.110)	(0.236)	(0.125)	(0.174)
Age 45-49	0.105**	0.129	0.113	0.248***	0.152	0.018	0.169	0.092
	(0.047)	(0.089)	(0.071)	(0.086)	(0.118)	(0.248)	(0.131)	(0.190)
Age 50-54	0.173***	0.195**	0.204***	0.332***	0.159	0.115	0.147	0.129
	(0.047)	(0.087)	(0.071)	(0.087)	(0.115)	(0.239)	(0.131)	(0.189)
Age 55-59	0.193***	0.167*	0.203***	0.343***	0.129	-0.026	0.223	0.071
	(0.053)	(0.093)	(0.077)	(0.101)	(0.123)	(0.265)	(0.137)	(0.193)
Male	0.138***	0.288***	0.031	0.141***	0.144***	0.181**	0.046	0.092*
	(0.018)	(0.039)	(0.025)	(0.029)	(0.039)	(0.085)	(0.044)	(0.051)
Primary education completed	0.014	0.119**	-0.049	0.026	-0.039	0.063	-0.121*	0.028
	(0.023)	(0.054)	(0.032)	(0.027)	(0.068)	(0.178)	(0.072)	(0.056)
Secondary education completed	0.122***	0.289***	0.041	0.097***	0.099*	0.178	-0.105*	0.093**
	(0.020)	(0.045)	(0.028)	(0.026)	(0.053)	(0.137)	(0.060)	(0.043)
Post-secondary education completed	0.257***	0.398***	0.189***	0.310***	0.303***	0.325**	0.109	0.271**
	(0.027)	(0.051)	(0.040)	(0.053)	(0.078)	(0.165)	(0.088)	(0.109)
Graduate	0.494***	0.423***	0.420***	0.787***	0.453***	0.329**	0.240***	0.471***
	(0.028)	(0.048)	(0.037)	(0.058)	(0.074)	(0.149)	(0.079)	(0.103)
Technical	0.490***	0.464***	0.503***	0.826***	0.834***	0.460***	0.319*	1.218***
	(0.072)	(0.099)	(0.106)	(0.253)	(0.230)	(0.159)	(0.193)	(0.391)
Job-related training	0.103***	0.035	0.135***	0.202***	0.233***	0.123**	0.219***	0.328***
	(0.020)	(0.027)	(0.029)	(0.056)	(0.053)	(0.060)	(0.057)	(0.115)
Married	0.035*	0.059	0.028	0.060*	0.098*	0.099	0.072	0.052
	(0.019)	(0.039)	(0.028)	(0.033)	(0.052)	(0.107)	(0.055)	(0.064)
Formal sector	0.146***	0.112***	0.216***	0.090***	0.004	0.010	-0.036	0.021
	(0.013)	(0.024)	(0.019)	(0.025)	(0.034)	(0.064)	(0.037)	(0.050)
Professional	0.485***	0.097	0.369***	1.026***	0.633***	0.452**	0.303**	0.986***
	(0.057)	(0.065)	(0.063)	(0.144)	(0.186)	(0.184)	(0.153)	(0.374)
Administrative	0.123***	0.063	0.149***	0.072	0.101	0.330*	0.027	-0.093
	(0.031)	(0.051)	(0.044)	(0.060)	(0.086)	(0.171)	(0.095)	(0.142)
Clerical	0.251***	0.142***	0.325***	0.262***	0.159*	0.347**	0.132	0.058
	(0.032)	(0.050)	(0.047)	(0.071)	(0.095)	(0.175)	(0.103)	(0.158)
Service	-0.024	-0.124	-0.024	-0.036	-0.298**	-0.458	-0.437***	-0.089
	(0.037)	(0.076)	(0.055)	(0.062)	(0.132)	(0.333)	(0.130)	(0.184)
Sales	-0.005	-0.039	-0.095**	0.017	-0.129	0.074	-0.250***	-0.147
	(0.034)	(0.062)	(0.047)	(0.057)	(0.090)	(0.195)	(0.096)	(0.132)
Agricultural labourer	0.262***	0.086	0.542***	-0.094	-0.434**	-1.212**	-0.181	-0.117
	(0.090)	(0.123)	(0.129)	(0.203)	(0.206)	(0.562)	(0.277)	(0.091)

(Continued)

Table A4. (Continued)

	Panel A: Muslim				**Panel B: Hindu**			
	OLS	0.10	0.50	0.90	OLS	0.10	0.50	0.90
Production labourer	-0.012	0.040	-0.074*	-0.014	-0.064	0.119	-0.109	-0.110
	(0.031)	(0.056)	(0.044)	(0.054)	(0.084)	(0.180)	(0.093)	(0.119)
Secondary industry	-0.160*	-0.281**	-0.144	-0.207	-0.644***	-1.738***	-0.294	0.003
	(0.087)	(0.113)	(0.127)	(0.201)	(0.204)	(0.566)	(0.270)	(0.104)
Tertiary industry	-0.143*	-0.238**	-0.134	-0.189	-0.652***	-1.769***	-0.306	0.145
	(0.085)	(0.110)	(0.124)	(0.200)	(0.206)	(0.566)	(0.272)	(0.103)
Urban	0.028**	-0.077***	0.023	0.175***	-0.012	-0.143**	-0.069*	0.181***
	(0.013)	(0.026)	(0.020)	(0.027)	(0.036)	(0.068)	(0.039)	(0.058)
Constant	3.045***	2.076***	3.196***	3.748***	3.519***	3.691***	3.663***	3.611***
	(0.102)	(0.159)	(0.148)	(0.219)	(0.249)	(0.644)	(0.318)	(0.218)
Observations	8,305	8,305	8,305	8,305	1,136	1,136	1,136	1,136
R^2	0.272	0.100	0.210	0.160	0.336	0.127	0.274	0.187

Notes: Robust standard errors are in parentheses. The result is rounded to three digits after the decimal. Included in the regression specification but not reported are number of children and dummy variables for region of residence. The results for counterfactual wage regression estimates $\hat{\beta}_{ct}$ are not reported. However, counterfactual wage distributions assume that men's returns to labour market characteristics apply for women, and therefore $\hat{\beta}_{ct}$ is comparable to $\hat{\beta}_{mt}$. A similar argument may apply the wage gap between Muslims and Hindus.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Author's calculation from the LFS dataset for 2009.