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This paper empirically examines the determinants of the gender wage gap across the wage distribution in rural Bangladesh, applying the Oaxaca–Blinder decomposition to the unconditional quantile regression approach. Using panel data from three rounds (2011–12, 2015, and 2019) of the Bangladesh Integrated Household Survey, this study controls for both household-level unobserved heterogeneity and selection bias in rural wage employment. Results reveal that the gender wage gap is most pronounced at the lower end of the distribution, providing strong evidence of the sticky floor phenomenon. We find that larger return to education and coefficient of full-time employment for females significantly contributed to a reduced wage gap at the upper end of the distribution, while larger return to education and coefficient of non-agricultural employment for females contributed to narrowing the wage gap at the lower end. Notably, as education is associated with a higher probability of wage employment for females, the contribution of education becomes stronger after controlling for selectivity bias. The findings suggest that promoting female education and expanding access to non-agricultural employment are key to reducing the gender wage gap in rural Bangladesh, although unobservable factors continue to perpetuate the sticky floor phenomenon.

Keywords: Education; Decomposition; Household fixed effects; Gender wage gap; Rural Bangladesh; Unconditional quantile regression

JEL classification codes: I24; I26; J31; J71

1. Introduction

In rural areas of developing countries, gender inequality in the participation and outcome in labor market opportunities remains a pressing issue, primarily due to structural disadvantages such as limited ownership of or access to land, assets, credit, and human capital (Ma et al., 2025; Sultana et al., 2024). Compared to other South Asian countries, including India and Pakistan, Bangladesh is often recognized for having a relatively smaller gender wage gap (Rahman & Al-Hasan, 2022). This achievement may be attributed to long-standing policy initiatives, such as a quota system for females in government jobs, investment in female education, and an overall socio-cultural perspective towards females (Asian Development Bank [ADB], 2004). Since gaining independence, Bangladesh has actively promoted gender equality in employment, resulting in a significant rise in female labor force participation, from 4.13% in 1974 (Bangladesh Bureau of Statistics [BBS], 2008) to 36.3% in 2016–17 (BBS, 2023). However, the lower gender wage gap is likely contributed to by manufacturing sectors, particularly in urban areas, whereas there is little existing research on the gender wage gap focusing on rural Bangladesh. Nevertheless, empowering females in rural areas is essential for achieving poverty reduction and gender equality, as implied in the United Nations Sustainable Development Goals No. 1 and 5 (United Nations, 2025).

This study analyzes the determinants of the gender wage gap at different points of the wage distribution in rural Bangladesh. Such analysis contributes to the literature by identifying segments of the distribution where the gaps are most pronounced, such as the “sticky floor” or “glass ceiling” phenomenon, and factors that either widen or mitigate the gaps. The “sticky floor” phenomenon refers to systemic barriers that confine females to low-paying jobs, leading to a wider wage gap at the lower end of the distribution. Conversely, the “glass ceiling” describes the underrepresentation of females in high-paying, managerial roles, where wage disparities widen at the upper end of the distribution. Empirically, the literature has analyzed the determinants of gender wage gaps across the distribution applying the Oaxaca–Blinder (O–B) decomposition (Blinder, 1973; Oaxaca, 1973) to quantile regression techniques. A comprehensive review of previous studies by Fang and Sakellariou (2015) found the prevalence of the glass ceiling phenomenon in developed countries and the sticky floor phenomenon in developing economies. For example, Chi and Li (2008) and Duraisamy and Duraisamy (2016) reported evidence of the sticky floor phenomenon in China and India.

The gender wage gap in Bangladesh has been widely examined across different datasets and sectors. Ahmed and Maitra (2010), using the nationwide Labor Force Survey (LFS) for 1999–2000, found larger wage gaps in urban compared to rural areas. Extending this research, Ahmed and McGillivray (2015), utilizing LFS data from 1999, 2005, and 2009 and applying unconditional quantile regression (UQR), reported a persistent sticky floor phenomenon, with some improvement noted in 2009. Consistent with these findings, Ahmed and Maitra (2015) used LFS data for 2005 and 2009 and found the sticky floor effect stronger than the glass ceiling. Rahman and Al-Hasan (2019), using the Quarterly Labor Force Survey (QLFS) 2015–16 and applying conditional quantile regression (CQR), also observed higher wage gaps at the lower end of the distribution, attributing this to the concentration of females in low-paying informal employment. Nordman et al. (2019) focused exclusively on the formal sector, using the Enterprise-based Skill Survey (ESS) for 2012. Utilizing UQR, they confirmed the sticky floor phenomenon after controlling for firm-specific effects. Faruk (2021), applying CQR and using QLFS 2016–17, also found a strong sticky floor and a weaker glass ceiling. Therefore, the existing literature overwhelmingly supports the presence of the sticky floor phenomenon in Bangladesh, although its significance varies depending on the data and sectors examined.

Despite this broad consensus, research on rural Bangladesh reveals a clear gap. No studies have decomposed the gender wage gap by individual variables focusing on rural areas, which exhibit distinct characteristics such as a lack of formal education, agricultural concentration, and persistent cultural expectations or religious norms (Sultana et al., 2024). Furthermore, the literature predominantly uses cross-sectional data, overlooking household-level unobserved heterogeneity. This oversight may lead to biased estimations of labor participation and wage outcomes, thereby limiting the understanding of rural gender wage disparities.

This paper empirically analyzes the determinants of the gender wage gap across the wage distribution in rural Bangladesh. We employ rich panel data from three rounds (2011–12, 2015, and 2019) of the Bangladesh Integrated Household Survey (BIHS) conducted by the International Food Policy Research Institute (IFPRI), controlling for household-level unobserved heterogeneity. This study applies the O–B decomposition to the UQR by Firpo et al. (2009), enabling the decomposition of gender wage gaps at different points of the distribution. Furthermore, given low participation in rural wage employment among females, we control for the non-random participation using Heckman's (1979) two-step procedure. To the best of our knowledge, this is the first detailed decomposition of the gender wage gap across the distribution in rural Bangladesh, controlling for household-level unobserved heterogeneity and non-random selection, thereby making a novel contribution to the literature.

This paper is organized as follows. Section 2 provides the empirical specification. Section 3 explains the data sources and sample construction used in the empirical analysis and presents the descriptive statistics. Section 4 presents the estimation results. Section 5 performs several robustness checks. The final section concludes the paper and presents its policy implications.

2. Empirical specification

2-1. Wage equation

To analyze the association between individual characteristics and wages, we pool data from three BIHS panels and estimate the wage equation. The main identification strategy involves incorporating household fixed effects, capturing time-invariant characteristics common to all household members. Although individual-level panel data can be constructed, individual fixed effects are not included because years of education are largely time-invariant.

In our analysis, we estimate the wage equation separately for males and females. Repeated observations of the same individual over different periods and/or observations of different individuals of the same gender within the same household (e.g., father-son or mother-daughter) share the same fixed effects. This approach partially controls for unobserved individual heterogeneity, because household members are more likely to share innate abilities than unrelated individuals (Ashenfelter & Zimmerman, 1997; López Bóo, 2010). Moreover, household fixed effects can capture family backgrounds and social networks that directly affects wages (Blunch, 2016).

Therefore, we estimate the following wage equation separately for males (*m*) and females (*f*):

(1) $\ln w_{ijht} = \alpha_j + \boldsymbol{X}'_{ijt}\boldsymbol{\zeta}_j + \eta_h + \varphi_t + \varepsilon_{ijht}$,

where $\ln w_{ijht}$ is the log hourly wages of individual *i* with gender *j* ($j = m, f$) affiliated with household *h* in survey year *t* ($t = 2011-12, 2015, and\ 2019$) deflated by national consumer price index (CPI) (2005–2006 = 1);[1] α_j is a constant term for gender *j*; $\boldsymbol{X}_{ijt}$ is a vector of individual characteristics including years of education, age, its square, a dummy for head of household, a dummy for married, a dummy for non-Muslims, a dummy for full-time workers (workers working more than 40 hours per week), a dummy for non-agricultural workers, and a dummy for working in urban areas;

[1] We sourced the data from Table 1.7 of the Bangladesh Bureau of Statistics (2021: 20–21), where CPIs have been constructed with 2005–06 as the base year.

η_h is household fixed effects; φ_t is survey year fixed effects; and ε_{ijht} is an error term. We estimate Equation (1) using robust standard errors clustered by household.

2-2. Decomposition of gender wage gap across the distribution

To explore the determinants of the gender wage gap across the distribution, we decompose the gender wage gap at each quantile into two components: one attributable to differences in explanatory variables (i.e., composition effect) and another attributable to the coefficients of these explanatory variables (i.e., wage structure effect). For this purpose, we employ the method proposed by Firpo et al. (2009) for estimating UQR, which allows the O–B decomposition at any unconditional quantiles. This extended O–B decomposition, employing the method by Firpo et al. (2009), allows analysis of whether the sticky floor phenomenon (i.e., gender wage gap at lower quantiles) or the glass ceiling phenomenon (i.e., gender wage gap at upper quantiles) prevails in rural Bangladesh, and it identifies the major factors contributing to these phenomena. Note that several studies (e.g., Duraisamy & Duraisamy, 2016; Faruk, 2021; Rahman & Al-Hasan, 2019) employ an alternative method based on CQR by Machado and Mata (2005) for the O–B decomposition across the wage distribution. However, the method by Machado and Mata (2005) does not decompose the composition effect into the contribution of each explanatory variable (Fortin et al., 2011). Considering that this study aims to identify the factors contributing to both wage structure and composition effects, the method by Firpo et al. (2009) has a clear advantage by allowing the subdivision of both effects into the contributions of individual explanatory variables.

The key procedure of this method involves replacing the observed value of a dependent variable with an estimated value of the re-centered influence function (RIF) for a given quantile. Subsequently, we conduct an ordinary least squares (OLS) regression of this new RIF value on the explanatory variables (i.e., UQR). The RIF value at the τ-th unconditional quantile of the dependent variable $\ln w_{ijht}$ is given by:

$$(2)\ RIF\left(\ln w_{ijht}, q_j^\tau\right) = q_j^\tau + \frac{\tau_j - I\left\{\ln w_{ijht} \le q_j^\tau\right\}}{f_{\ln w_{ijht}}(q_j^\tau)},$$

where q_j^τ is the τ-th unconditional quantile of the dependent variable $\ln w_{ijht}$ of a given gender j; $I(\cdot)$ is an indicator function taking a value of 1 if the condition is satisfied and 0 otherwise; and $f_{\ln w_{ijht}}\left(q_j^\tau\right)$ is the density of the marginal distribution of $\ln w_{ijht}$ evaluated at q_j^τ. Given that the expectation of RIF at the τ-th unconditional quantile is equal to the variable's τ-th unconditional quantile and the law of iterated expectations applies in the case of RIF values, the estimated coefficients of the UQR indicate a marginal effect on $\hat{q}_j^\tau$ (see Firpo et al., 2009):

$$(3)\ \hat{q}_j^\tau = \mathrm{E}\left[\widehat{RIF}(\ln w_{ijht}, q_j^\tau)\right] = \mathrm{E}\left[\mathrm{E}\left(\widehat{RIF}(\ln w_{ijht}, q_j^\tau)\middle|\boldsymbol{Z}_{ijht}\right)\right] = \overline{\boldsymbol{Z}}'_{ijht}\widehat{\boldsymbol{\beta}}_j^\tau\ ,$$

where $\hat{q}_j^\tau$ is the unconditional sample quantile of the dependent variable; $\widehat{RIF}(\ln w_{ijht}, q_j^\tau)$ is the estimated RIF value obtained by substituting the estimated $\hat{q}_j^\tau$ and $\hat{f}_{\ln w_{ijht}}(\hat{q}_j^\tau)$ into Equation (2); $\boldsymbol{Z}_{ijht}$ is a vector of all explanatory variables in Equation (1); $\widehat{\boldsymbol{\beta}}_j^\tau$ is a vector of the estimated coefficients of the UQR at the τ-th quantile of a given gender j; and the bar over the term denotes the mean.

The gender wage gap at τ-th quantile can be decomposed similarly to the standard O–B decomposition at the mean. This is achieved by adding and subtracting the counterfactual wage quantile for females $\hat{q}_{fc}^\tau = \overline{\boldsymbol{Z}}'_{ifht}\widehat{\boldsymbol{\beta}}_m^\tau$, which represents the wage that females would receive under the non-discriminatory wage structure (i.e., male wages) at a given quantile. The decomposition is expressed as:

$$(4)\ \hat{q}_m^\tau - \hat{q}_f^\tau = \left(\hat{q}_m^\tau - \hat{q}_{fc}^\tau\right) - \left(\hat{q}_f^\tau - \hat{q}_{fc}^\tau\right)$$

$$= \left(\overline{\boldsymbol{Z}}'_{imht}\widehat{\boldsymbol{\beta}}_m^\tau - \overline{\boldsymbol{Z}}'_{ifht}\widehat{\boldsymbol{\beta}}_m^\tau\right) - \left(\overline{\boldsymbol{Z}}'_{ifht}\widehat{\boldsymbol{\beta}}_f^\tau - \overline{\boldsymbol{Z}}'_{ifht}\widehat{\boldsymbol{\beta}}_m^\tau\right)$$

$$= (\overline{\boldsymbol{Z}}'_{imht} - \overline{\boldsymbol{Z}}'_{ifht})\widehat{\boldsymbol{\beta}}^{\tau}_{m} + \overline{\boldsymbol{Z}}'_{ifht}(\widehat{\boldsymbol{\beta}}^{\tau}_{m} - \widehat{\boldsymbol{\beta}}^{\tau}_{f}).$$

In Equation (4), the first term on the last line of the right-hand side represents the composition effect, which captures the gender wage gap at the τ-th quantile attributable to the differentials in the average individuals' characteristics. The second term represents the wage structure effect, which captures the gender wage gap at the τ-th quantile attributable to the differentials in the coefficients of explanatory variables. Note that the results of the above-decomposition are dependent on the choice of the non-discriminatory wage structure (i.e., the reference wage category). Following Ahmed and McGillivray (2015), we have selected male wages as the reference category. This choice can be at least partially justified by the fact that male wages are usually used as the non-discriminatory wages under legal framework, and the majority of wage earners in rural Bangladesh are male. We will present the estimation results based on an alternative category in a robustness check in Section 5.

2-3. Selection-bias corrections

The wage equation and decomposition are applied only to wage earners with observable wages. However, as the selection into the wage earners is unlikely to be random, the estimated coefficients can be biased. This issue is particularly relevant for females, because the share of participation is remarkably low. Thus, following Ahmed and McGillivray (2015) and Murakami and Nomura (2023), we apply Heckman's (1979) two-step procedure to correct the selection bias. To estimate the selection equation, we include the following non-participants: unemployed, household workers, and wage earners who did not report any income or working hours.

First, we separately estimate a Probit selection equation separately for males and females, using the sample of adults aged 18 to 65 years:

$$(5)\ L_{ijht} = I\{\boldsymbol{H}'_{ijht}\boldsymbol{\gamma}_j + \xi_h + \mu_t + u_{ijht} > 0\},$$

where L_{ijht} is a binary variable, taking a value of 1 if an individual *i* becomes a wage earner and 0 otherwise; $\boldsymbol{H}_{ijht}$ is a vector of explanatory variables that determine wage-earner participation; ξ_h is household fixed effects; μ_t is survey year fixed effects; and u_{ijht} is an error term. The standard deviation of the error term σ_{uj} is normalized to 1. We include the following exclusion restrictions, which are included in the vector $\boldsymbol{H}$ in Equation (5) but not included in the vector $\boldsymbol{X}$ in Equation (1): the sum of real non-labor income of a household *h* (measured in thousand taka), the sum of real wages in *h* excluding those of an individual *i* (in thousand taka), the number of wage earners in *h* excluding *i*, the number of children aged five years or younger in *h*, and the number of elderly aged 65 years or older in *h*.

Following Papke and Wooldridge (2008), we add household-level time averages of all explanatory variables and year dummies to control for the household-level time-invariant unobserved heterogeneity. We estimate the pooled Probit model with time averages using robust standard errors clustered by household, allowing serial correlation within each household. From this equation, we obtain the inverse Mills ratio $\hat{\lambda}_{ij} = \frac{\phi(\boldsymbol{\Gamma}'_{ijht}\hat{\boldsymbol{\delta}}_j)}{\Phi(\boldsymbol{\Gamma}'_{ijht}\hat{\boldsymbol{\delta}}_j)}$, where $\boldsymbol{\Gamma}_{ijht}$ denotes all explanatory variables in Equation (5), while ϕ and Φ are the density and cumulative distribution functions of the standard normal distribution, respectively.

Second, we include the estimated selectivity correction term as an additional variable in Equation (1):

$$(6)\ \ln w_{ijht} = \alpha_j + \boldsymbol{X}'_{ijt}\boldsymbol{\zeta}_j + \theta_j\hat{\lambda}_{ij} + \eta_h + \varphi_t + v_{ijht}\ ,$$

where θ_j is the covariance between the error terms of Equation (1) and Equation (5),[2] and v_{ijht} is the error term.

Thus, the gender wage gap at the τ-th quantile, after incorporating the selectivity correction term, is decomposed as follows:

(7) $\hat{q}_m^{\tau} - \hat{q}_f^{\tau} = (\bar{\boldsymbol{Z}}'_{imht} - \bar{\boldsymbol{Z}}'_{ifht})\hat{\boldsymbol{\beta}}_m^{\tau} + \bar{\boldsymbol{Z}}'_{ifht}\left(\hat{\boldsymbol{\beta}}_m^{\tau} - \hat{\boldsymbol{\beta}}_f^{\tau}\right) + \hat{\theta}_m(\bar{\lambda}_{im} - \bar{\lambda}_{if}) + (\hat{\theta}_m - \hat{\theta}_f)\bar{\lambda}_{if}$.

3. Data sources, sample construction, and descriptive statistics

The data utilized in this study is the three-round unbalanced panel data from the BIHS. This survey is the sole nationally representative survey covering only rural Bangladesh, excluding any urban or peri-urban zones.[3] It represents the rural areas of the seven (now eight) administrative divisions: Barishal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur, and Sylhet. The IFPRI conducted the first round of the survey from November 2011 to March 2012. Subsequently, the second and third rounds were conducted from January to June 2015 and from January to June 2019, respectively.[4] These three rounds of the survey were administered to the same sample of households, thereby constituting

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[2] As $\sigma_{uj} = 1$, $\theta_j = \mathrm{cov}(u_{ijht}, \varepsilon_{ijht}) = \rho_j \sigma_{\varepsilon j}$, where ρ denotes the correlation coefficient between the error terms of the wage and selection equations.

[3] The survey consistently defines rural areas as non-municipal, non-city areas, following BBS's national definition.

[4] The dataset of the BIHS by the IFPRI for the years 2011–12, 2015, and 2019 has been utilized from https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/21266, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/BXSYEL, and https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/NXKLZJ.

a three-round panel survey.[5]

Several stages of data cleaning were undertaken for this research. In the initial step, we excluded observations with unmatched household identification numbers, as the BIHS survey for each year consists of multiple modules, and the variables therein should be merged based on these identification numbers. In constructing the exclusion restriction, variables included solely in vector $\boldsymbol{H}$ of Equation (5) were not subjected to further data cleaning.[6] After the construction of the exclusion restriction variables, we limit the sample included in the selection equation to adults aged between 18 and 65 years, who are expected to continuously participate in the labor force. Additionally, the selection equation excluded self-employed, unpaid workers, current students, and those reporting the reasons for not seeking employment as studentship, underage, old age, disability, and unknown. However, the exclusion of self-employed may cause an additional selectivity bias because the share is large in rural Bangladesh. To address this bias, we will include self-employed and unpaid workers in the selection equation and estimate it using a multinomial logit model in a robustness check in Section 5. Furthermore, we excluded households consisting of only one individual of a given gender to include the household fixed effects. The non-labor income consists of rent received from land and other property, income from insurance, profits and dividends, gratuity and retirement benefits, lottery, charity, interest from banks and other sources,

[5] The BIHS dataset shows minimal attrition from one round to another, with the percentage being notably low.

[6] This is because the wages of individuals aged over 65, who are excluded from the selection and wage equations, are also likely to affect the labor participation of individuals aged between 18 and 65 years.

other received cash, and income from other assets. We add remittances to the non-labor income. Consistent with wages, the non-labor income is also deflated by the national CPI (2005–2006 = 1).

Subsequently, we exclude observations with missing or unspecified values for variables in the wage equation. Hourly wages are calculated by dividing the monthly income of wage earners—defined as individuals reporting daily wage or salary work as their nature of work—by the total monthly hours worked. Given that the survey provides only average daily hours and weekly working days, we approximate the monthly hours as weekly hours multiplied by four. Additionally, many wage earners reported income and working hours as self-employed; hence, we exclude these from monthly income and hours in the wage calculation.

Regarding the explanatory variables included in vector $\boldsymbol{X}$ in Equation (1), we derive the years of education from a variable indicating an individual's educational achievements.[7] The dummy for married is created from a variable indicating marital status, with never married, widow/widower, divorced, separated/deserted as the reference category. The dummy for non-Muslims, consisting of Hindus and Christians, is created from a variable indicating the household head's religion. The dummy for non-agricultural workers, including non-agricultural manual workers, service and

[7] The original variable indicates the highest class category that an individual passed. We construct the years of education as follows. We consider individuals with no formal education, those who completed primary education, those who completed secondary education or having a Secondary School Certificate (SSC), those having a Higher Secondary Certificate (HSC), those having a diploma, and those who completed tertiary education as having zero, five, 10, 12, 14, and 16 years of education, respectively.

professional workers, and other small business workers, is created from a variable indicating occupation categories. We note that the employment-related variables in vector $\boldsymbol{X}$ in the wage equation (the dummy for full-time workers, the dummy for non-agricultural workers, and the dummy for working in urban areas) are not included in vector $\boldsymbol{H}$ in the selection equation, whereas other variables in vector $\boldsymbol{X}$ are also included in vector $\boldsymbol{H}$. Finally, after applying the data cleaning for the construction of used variables, we excluded households consisting of only one wage earner of a given gender.

Table 1 reports the details of the sample selection by gender. The share of participation in wage earners for males was remarkably high (consistently exceeding 97%) from 2011 to 2019, whereas the share for females was considerably low (consistently around 15%). The stable participation share justifies our identification strategy for pooling samples across three periods and including household fixed effects.

Table 2 presents the descriptive statistics of the pooled sample from 2011 to 2019, categorized by gender and further disaggregated into wage earners and non-participants. The numbers of observations of wage earners for males and females are 4,820 and 657, respectively, totaling 5,477.[8] We find that male wage earners tend to have fewer years of education, are older, and have substantially lower non-labor income compared to male non-participants. Similar trends are observed for females. Notably, female wage earners tend to have remarkably fewer children aged five years or younger

[8] The numbers of distinct households are 1,823 and 283 for males and females, respectively. Note that split households that separated from an original household are assigned identical household identification numbers.

compared to female non-participants, suggesting that the number of children is a significant determinant for the participation in wage earners.

In comparing male and female wage earners, males have longer years of education, a higher share of heads of households, and a higher share of married workers, as expected. Interestingly, females demonstrate a higher share of non-Muslims and non-agricultural workers. The former may suggest that cultural or community-level factors influence female labor participation among religious minorities, where female Christians and Hindus are more likely to participate in the labor market compared to Muslim females, potentially due to the *purdah* norms, keeping females in the confinement of their homes (Heintz at al., 2018).

Figure 1 shows the log-hourly wage distribution of the pooled sample by gender. We find that share of low-wage earners is relatively high for females, and the wage distribution for females is right-skewed. The average log hourly wages for males and females are 2.746 and 2.046, respectively, showing that the gender wage gap is more than 70% on average.

[Insert Tables 1 and 2 here]

[Insert Figure 1 here]

4. Estimation results

4-1. Selection equation

Table 3 presents the estimation results of Equation (5) by gender. The results reveal gender-specific responses to education and household characteristics in determining wage labor participation. Interestingly, years of education are associated with a lower probability of wage employment for males, whereas for females, education significantly increases their likelihood of wage labor participation after controlling for household fixed effects. Although this finding contradicts that of Ahmed and McGillivray (2015), our findings likely reflect the labor market realities in rural Bangladesh. Higher education among males possibly leads to job selectivity, causing avoidance of wage-based work, which may be due to the lack of formal structure or lower level of salaries associated with such work in rural areas. On the contrary, education for females plays an enabling role, helping them overcome social constraints, build and utilize skills, and access labor opportunities beyond their household responsibilities.

We find that marital status and number of children significantly affect females' wage labor participation. Marriage and dependent children are associated with a statistically significant reduction in participation, whereas for males, these variables are negative but not statistically significant. Similar to Heintz et al. (2018), this result aligns with prevailing gender norms and the division of labor within households in rural Bangladesh, where married women are expected to prioritize domestic responsibilities and childbearing, especially when alternative family income sources exist. Indeed, the number of other wage earners also negatively affects females' participation, indicating that females may voluntarily withdraw from the labor market, aligned with traditional gender-related expectations and a lack of childcare services in rural areas.

[Insert Table 3 here]

4-2. Wage equation

Table 4 presents the estimation results of the wage equation both without and with the selectivity correction term, as presented by Equations (1) and (6), respectively. We find that the return to an additional year of education for males is 2.41% and highly significant without the household fixed effects. However, once they are included, the return significantly reduces and becomes insignificant.

The opposite scenario is prominent for females. They receive significantly higher wages with an additional year of education, irrespective of controlling for household fixed effects. Moreover, when they are controlled, the return to education increases from 7.73% to 11.04%. This finding is consistent with Ahmed and McGillivray (2015), who find that returns to primary and secondary education are higher for females than for males in Bangladesh. However, the novel contribution of this study lies in demonstrating that this disparity becomes more pronounced when household fixed effects are controlled. This indicates that unobservable time-invariant household characteristics, which increase its members' wages, are negatively correlated with its female members' years of education; thus, the returns to education for females are underestimated when household fixed effects are not controlled.

Additionally, we find that the coefficient on the dummy for full-time workers is negative and significant for both males and females, with the coefficient consistently larger for males in absolute values.

[Insert Table 4 here]

4-3. Decomposition of gender wage gap across the distribution

Based on Equation (4), Figure 2 illustrates the overall gender wage gap from the 5th to 95th quantiles, disaggregated into composition and wage structure effects. The estimation results of the UQR, as specified by Equation (3), are reported in Table A1 in the Appendix. Furthermore, Table A2 provides a detailed decomposition of the gender wage gap into composition and wage structure for each explanatory variable.

The overall gender wage gap is most pronounced at the lower end of the wage distribution, with a magnitude of 0.8097 log points at the 10th quantile, narrowing significantly to 0.3212 log points at the 90th quantile (see Figure 2 and Table A2). This slope strongly supports the presence of a sticky floor phenomenon, where females face structural disadvantages in accessing better-paying opportunities at the lower end of the wage distribution. These findings are consistent with those of Ahmed and Maitra (2015), Ahmed and McGillivray (2015), Faruk (2021), and Rahman and Al-Hasan (2019), who also find the presence of a sticky floor phenomenon from the analysis covering both urban and rural Bangladesh.

The decomposition of the gender wage gap across the distribution highlights the evolution of wage structure and composition effects at different quantiles. The wage structure effect demonstrates a declining trend from the lower to upper ends. Specifically, at the 10th quantile, the wage structure effect is estimated at 0.9927 log points, representing more than overall gender wage gap at that quantile (0.8097) (see Table A2). Thus, the lower quantile gaps are primarily driven by differences in how labor market characteristics are rewarded for males and females. However, this effect diminishes consistently and becomes negative (-0.0773 log points) at the 90th quantile, suggesting that at higher wage levels, the wage structure effect contributes less, or even inversely, to the observed gender wage gap.

In contrast, the composition effect reveals an opposite trend. At the 10th quantile, it is -0.1831 log points, which should have reduced the wage gap but was offset by the wage structure effect. By the 90th quantile, the composition effect increases to 0.3985 log points, signifying that more than the overall gender wage gap at the quantile (0.3212) is explained by differences in observable characteristics between males and females (see Table A2).

An important contribution of this study is to decompose the wage gap into the impact of individual explanatory variables, which provides essential insights into the drivers of inequality. We find that the wage structure effects of years of education and the full-time employment dummy are largely significant across quantiles. Additionally, the non-agricultural sector dummy is significant at several quantiles (see Figure 3 and Table A2). By contrast, the composition effects of these three variables are either insignificant across quantiles or remarkably small (see Table A2).[9]

The wage structure effect of years of education is particularly notable. We find that it significantly decreases the gender wage gap at both the lower and upper ends of the wage distribution. The returns to education for females are significantly higher than those for males at both the lower and upper ends of the wage distribution, contributing to narrowing the gender wage gap in these segments (see Figure 3). Specifically, the estimated returns to education for females reach 15.32% at the 10th quantile and increases further to 26.24% at the 90th quantile. In contrast, the returns for males at these quantiles are statistically insignificant and almost zero (see Table A1). Interestingly, the lower returns to education for females in the middle of the distribution (between the 25th and 75th quantiles) suggest that education is particularly empowering for females at both the most and least advantaged positions within the rural labor market.

A similar trend is observed for the full-time employment dummy. The negative wage structure effect implies that full-time employment significantly reduces male earnings relative to females, particularly at the upper end of the distribution, thereby contributing to narrowing the gender wage gap at the upper quantiles (see Figure 3).

Focusing on sectoral differences, we find that the wage structure effect of the non-agricultural employment dummy is significantly negative at the 15th, 20th, and 25th quantiles (see Figure 3). This suggests that females in non-agricultural sectors at

[9] Thus, we show only the wage structure effects in Figure 3 and subsequent figures.

the lower end of the distribution receive relatively higher wages, highlighting the sectors' mitigating role in the gender wage gap at the lower end.

Using Equation (7), Figure 4 presents the decomposition results for the wage structure effects after incorporating the selectivity correction term. The estimation results of the UQRs and the detailed decomposition of each explanatory variable are presented in Tables A3 and A4, respectively. As the correction term is largely insignificant across the quantiles (see Table A4), it is not illustrated in Figure 4.[10] We find that its inclusion does not substantially alter the previous finding. The wage structure effects of education, full-time employment, and non-agricultural employment remain consistent with the initial results illustrated in Figure 3. Importantly, the selectivity correction term is insignificant but largely positive at the lower and upper quantiles for females (see Table A3), unlike the mean regression presented in column

[10] Although the composition effect of the inverse Mills ratio is also largely insignificant, following Equation (14) of Neuman and Oaxaca (2004: 8), it is possible to further decompose the effect by introducing the following counterfactual inverse Mills ratio for females, where females would face the same coefficients of the selection equation faced by males: $\hat{\lambda}^c_{if} = \frac{\phi(\boldsymbol{\Gamma}'_{ifht}\hat{\boldsymbol{\delta}}_m)}{\Phi(\boldsymbol{\Gamma}'_{ifht}\hat{\boldsymbol{\delta}}_m)}$. Consequently, the correction term is decomposed as $\hat{\theta}_m\bar{\lambda}_{im} - \hat{\theta}_f\bar{\lambda}_{if} = \hat{\theta}_m(\bar{\lambda}_{im} - \bar{\lambda}_{if}) + (\hat{\theta}_m - \hat{\theta}_f)\bar{\lambda}_{if} = \hat{\theta}_m(\bar{\lambda}_{im} - \bar{\lambda}^c_{if}) + \hat{\theta}_m(\bar{\lambda}^c_{if} - \bar{\lambda}_{if}) + (\hat{\theta}_m - \hat{\theta}_f)\bar{\lambda}_{if} = \hat{\theta}_m(\bar{\lambda}_{im} - \bar{\lambda}^c_{if}) + (\hat{\theta}_m\bar{\lambda}^c_{if} - \hat{\theta}_f\bar{\lambda}_{if})$. Therefore, we refer to $\hat{\theta}_m(\bar{\lambda}_{im} - \bar{\lambda}^c_{if})$ and $\hat{\theta}_m\bar{\lambda}^c_{if} - \hat{\theta}_f\bar{\lambda}_{if}$ as the revised composition and wage structure effects of the inverse Mills ratio. Figure A1 in the Appendix adds the revised wage structure effect to the original Figure 4. We confirm that as the coefficient of the selectivity correction term in the wage equation is positive for females and negative for males at lower quantiles, the term also contributes to narrowing the gender wage gap at the lower ends of the wage distribution.

[6] of Table 4. Thus, the returns to education for females further increase after controlling for the selectivity term. Therefore, the wage structure effect of education also increases in absolute values from -0.4820 to -0.5146 at the 10th quantile and from -0.5067 to -0.5552 at the 85th quantile (see Tables A2 and A4). Consequently, after accounting for the selectivity bias, the wage structure effects of education and full-time employment continue to contribute to narrowing the gender wage gap at both the lower and upper ends of the distribution. The wage structure effect of non-agricultural employment also contributes to narrowing the wage gap at the lower end of the distribution.

However, results reveal that unobservable factors continue to exert a strong influence, particularly at the lower end of the distribution. Evidently, a large and statistically significant positive constant term contributes to widening the gender wage gap in the lower quantiles, such as the 10th and 15th (see Table A4). Therefore, this finding reinforces the persistence of the sticky floor phenomenon, where structural and systemic barriers disproportionately disadvantage females in low-wage segments, even after controlling for household fixed effects and selection bias.

[Insert Figures 2, 3 and 4 here]

5. Robustness checks

5-1. Pooling male and female samples

One possible concern regarding the results is that males and females at the same quantiles may not be comparable due to the low wage labor participation for females. We have already incorporated the selectivity correction term in the wage equation, showing that this term is insignificant for females. Nevertheless, the higher returns to education for females at the lower quantiles raise concerns that the sample may not accurately represent the wage distribution of the entire population. To address this issue, we pooled the male and female samples and estimated the UQR, adding a female dummy and interaction terms between the female dummy and the three main variables (years of education, full-time employment dummy, non-agricultural employment dummy). This approach allows us to examine the coefficients of the interaction terms at the same wage quantiles for both males and females.[11]

Figure 5 demonstrates the estimation results, while Table A5 in the Appendix shows the full set of coefficients and standard errors. We find that the interaction term between the female dummy and education is significantly positive at the lower end of the distribution including both males and females. Additionally, we find that the interaction term with the non-agricultural employment dummy is significantly positive at several lower quantiles, while the term with the full-time employment dummy is positive and larger at higher quantiles, supporting the main results presented in Section 4. Moreover, we find that the negative female dummy is most pronounced at lower quantiles, which is consistent with the larger wage structure effect of constant term observed at these lower quantiles.

[Insert Figure 5 here]

5-2. Alternative reference category

As specified by Equation (4) and explained in Section 2-2, we chose male wages as the reference category for the O–B decomposition analysis. However, the results depend on the choice of the reference category. Particularly, Neumark (1988) argues that the non-

[11] In this case, we pool the male and female samples in the selection equation for the calculation of the inverse Mills ratio.

discriminatory wage structure should be based on the coefficients obtained from a pooled regression of both male and female samples. Thus, following the argument, we use the estimated coefficients from the pooled regression $\widehat{\boldsymbol{\beta}}^{\tau}_{pool}$ as the non-discriminatory wages. In this case, the gender wage gap at the τ-th quantile is decomposed as follows:

$$(8)\ \hat{q}^{\tau}_{m} - \hat{q}^{\tau}_{f} = (\overline{\boldsymbol{Z}}'_{imht} - \overline{\boldsymbol{Z}}'_{ifht})\widehat{\boldsymbol{\beta}}^{\tau}_{pool} + \overline{\boldsymbol{Z}}'_{imht}\left(\widehat{\boldsymbol{\beta}}^{\tau}_{m} - \widehat{\boldsymbol{\beta}}^{\tau}_{pool}\right) + \overline{\boldsymbol{Z}}'_{ifht}\left(\widehat{\boldsymbol{\beta}}^{\tau}_{pool} - \widehat{\boldsymbol{\beta}}^{\tau}_{f}\right).$$

In Equation (8), the second and third terms represent the wage structure effect.

Based on Equation (8), Figures 6 and 7 illustrate the composition and wage structure effects of selected explanatory variables in the estimation without and with the selectivity correction term. The results are remarkably similar to those obtained using male wages as the reference category, as illustrated in Figures 3 and 4.[12] Consequently, we conclude that our findings regarding the contribution of the main explanatory variables are robust to the choice of the reference category in the O–B decomposition.

[Insert Figures 6 and 7 here]

5-3. Inclusion of self-employed and unpaid workers in the selection equation

As explained in Section 2-3, we excluded self-employed and unpaid workers from the selection equation in advance, which may introduce an additional selectivity bias. To address this bias, we included them into the selection equation and estimated it using a multinomial logit model. In this analysis, we treat unpaid workers as non-participants. Thus, the sample for the selection equation consists of non-participants, self-employed,

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[12] Tables A6 and A7 in the Appendix present the detailed decomposition of each explanatory variable.

and wage earners. Due to this inclusion, the number of observations in the selection equation increased from 4,938 to 12,992 for males and from 4,495 to 20,528 for females, respectively (for more details, see Table A8).

For the calculation of the selectivity correction terms, we follow Dubin and McFadden's (1984) method. In this method, the selectivity correction term for the reference category (i.e., wage earners, *Selectivity1*), whose outcome variable is observed in the wage equation, is calculated as $-\ln(p_{ijht})$, where p_{ijht} is the estimated probability of each category derived from the multinomial logit model.[13] For other categories (i.e., non-participants and self-employed, *Selectivity2* and *Selectivity3*, respectively) whose outcome variables are not observed, the selectivity correction terms are calculated as $\frac{p_{ijht}\ln(p_{ijht})}{1-p_{ijht}}$. We use the same exclusion restriction variables as in the Probit model.

The estimation results of the multinomial logit model are presented in Table A9.[14] Consistent with the results of the Probit equation in Table 3, the years of education are associated with a lower probability of non-participation and self-employment among females, whereas this variable is insignificant for males. Marriage, the number of children, and the presence of other wage earners are associated with a higher probability of non-participation and self-employment exclusively for females.

After controlling for the three selectivity terms, Figure 8 illustrates the total composition and wage structure effects, while Figure 9 illustrates the wage structure

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[13] For more details, see Equation 2.6 of Bourguignon et al. (2007: 178).

[14] The Hausman test for independence of irrelevant alternatives (IIA) is not rejected for females, whereas it is rejected for males.

effects of selected explanatory variables, after controlling for the three selectivity terms.[15] Consistent with the main result in Figure 2, Figure 8 shows a declining trend in the wage structure effect and an increasing trend in the composition effect from the lower to upper ends of the wage distribution. Furthermore, the contribution of our main explanatory variables in Figure 9 is similar to that in Figure 4. Therefore, we conclude that our main findings are robust to the inclusion of self-employed and unpaid workers in the selection equation.

[Insert Figures 8 and 9 here]

6. Concluding remarks

Using panel data from three rounds (2011–12, 2015, and 2019) of the nationally representative BIHS survey, this study empirically analyzed the determinants of the gender wage gap across the wage distribution in rural Bangladesh. For this purpose, the study applied the O–B decomposition to the UQR, decomposing gender wage gaps into composition and wage structure effects of individual explanatory variables across the distribution. Furthermore, we controlled for both household-level unobserved heterogeneity and non-random selection in wage employment.

We found that the overall gender wage gap is most pronounced at the lower end of the distribution, providing strong evidence of the sticky floor phenomenon in rural Bangladesh. Furthermore, the evolution of the overall gender wage gap across the distribution is primarily linked to the evolution of the wage structure effect.

[15] Tables A10 and A11 in the Appendix present the estimation results of the UQR and detailed decomposition of each explanatory variable, respectively.

The decomposition into individual explanatory variables revealed major factors mitigating the gender wage gap. We found that the wage structure effects of education and full-time employment contributed to the smaller wage gap at the upper end of the distribution. Moreover, the wage structure effects of education and non-agricultural employment contributed to narrowing the wage gap at the lower end of the distribution. Furthermore, as education is associated with a higher probability of wage employment, we found that the inclusion of the selectivity correction term amplifies the contribution of the wage structure effect of education in narrowing the wage gap. Given an increase in the years of education for females during the analysis period, we conclude that education played an enabling role in enhancing labor participation and wages, thereby reducing the gender wage gap, even in rural areas. However, as evidenced by a large and significant positive constant term, we found that unobservable factors continue to play a substantial role in sustaining the sticky floor phenomenon in rural Bangladesh.

Given the similarities in rural areas of Asian developing countries, including the predominance of small-scale agriculture (Ma et al., 2025), our finding provides relevant policy implications for those countries. Policymakers in those countries need to further emphasize rural education and non-agricultural employment for women through rural education scholarships and support for rural entrepreneurship. Such policies will eliminate internal structural constraints to sustainable development, thereby contributing to overcoming middle-income traps.

Finally, although we controlled for household fixed effects, we were unable to completely control for individuals' unobserved abilities and skills. Such an analysis is beyond the scope of this study; however, it presents an interesting subject for future research.

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Table 1. Sample selection of each year by gender.

	2011		2015		2019		Total	
	Males	Females	Males	Females	Males	Females	Males	Females
Non-participants	39	1418	36	1327	43	1093	118	3838
Wage earners	1658	214	1747	256	1415	187	4820	657
Total	1697	1632	1783	1583	1458	1280	4938	4495

Source: Authors' own calculations based on data from three rounds (2011–12, 2015, and 2019) of Bangladesh Integrated Household Survey.

Table 2. Descriptive statistics of the pooled sample by gender.

	Males														
	Wage earners					Non-participants					Total				
	Observations	Mean	Standard deviation	Min	Max	Observations	Mean	Standard deviation	Min	Max	Observations	Mean	Standard deviation	Min	Max
Log hourly wages	4,820	2.746	0.705	-1.502	7.279										
Years of education	4,820	3.527	4.129	0.000	16.00	118	5.847	4.471	0.000	16.00	4,938	3.582	4.152	0.000	16.00
Age	4,820	36.84	12.02	18.00	65.00	118	33.64	13.87	18.00	65.00	4,938	36.76	12.07	18.00	65.00
Age squared	4,820	1502	946.7	324.0	4225	118	1323	1103	324.0	4225	4,938	1497	951.0	324.0	4225
Head of household	4,820	0.740	0.439	0.000	1.000	118	0.475	0.501	0.000	1.000	4,938	0.734	0.442	0.000	1.000
Married	4,820	0.827	0.378	0.000	1.000	118	0.585	0.495	0.000	1.000	4,938	0.821	0.383	0.000	1.000
Non-Muslims	4,820	0.139	0.346	0.000	1.000	118	0.161	0.369	0.000	1.000	4,938	0.139	0.346	0.000	1.000
Full-time workers	4,820	0.579	0.494	0.000	1.000										
Non-agricultural workers	4,820	0.483	0.500	0.000	1.000										
Working in urban areas	4,820	0.129	0.336	0.000	1.000										
Inverse Mills ratio	4,820	0.052	0.052	0.000	0.533										
Sum of non-labor income	4,820	4.507	19.59	0.000	594.0	118	18.75	62.42	0.000	494.9	4,938	4.848	21.72	0.000	594.0
Sum of wages of other family members	4,820	0.867	1.807	0.000	27.84	118	1.096	1.911	0.000	8.892	4,938	0.873	1.809	0.000	27.84
Number of wage earners	4,820	0.395	0.648	0.000	4.000	118	0.449	0.687	0.000	3.000	4,938	0.397	0.649	0.000	4.000
Number of children	4,820	0.609	0.740	0.000	5.000	118	0.695	0.790	0.000	3.000	4,938	0.611	0.741	0.000	5.000
Number of elderly	4,820	0.172	0.416	0.000	2.000	118	0.212	0.431	0.000	2.000	4,938	0.173	0.416	0.000	2.000

	Females														
	Wage earners					Non-participants					Total				
	Observations	Mean	Standard deviation	Min	Max	Observations	Mean	Standard deviation	Min	Max	Observations	Mean	Standard deviation	Min	Max
Log hourly wages	657	2.046	0.909	-3.273	5.986										
Years of education	657	3.143	4.940	0.000	16.00	3,838	4.801	3.866	0.000	16.00	4,495	4.558	4.082	0.000	16.00
Age	657	39.02	10.46	18.00	65.00	3,838	34.78	14.12	18.00	65.00	4,495	35.40	13.73	18.00	65.00
Age squared	657	1631	854.9	324.0	4225	3,838	1409	1127	324.0	4225	4,495	1441	1094	324.0	4225
Head of household	657	0.326	0.469	0.000	1.000	3,838	0.139	0.346	0.000	1.000	4,495	0.167	0.373	0.000	1.000
Married	657	0.601	0.490	0.000	1.000	3,838	0.803	0.398	0.000	1.000	4,495	0.774	0.418	0.000	1.000
Non-Muslims	657	0.294	0.456	0.000	1.000	3,838	0.138	0.344	0.000	1.000	4,495	0.160	0.367	0.000	1.000
Full-time workers	657	0.572	0.495	0.000	1.000										
Non-agricultural workers	657	0.661	0.474	0.000	1.000										
Working in urban areas	657	0.100	0.301	0.000	1.000										
Inverse Mills ratio	657	1.143	0.555	0.091	4.498										
Sum of non-labor income	657	5.050	26.27	0.000	425.3	3,838	27.27	72.81	0.000	1470	4,495	24.02	68.47	0.000	1470
Sum of wages of other family members	657	1.470	2.975	0.000	48.02	3,838	1.304	2.404	0.000	23.20	4,495	1.328	2.496	0.000	48.02
Number of wage earners	657	0.629	0.776	0.000	4.000	3,838	0.441	0.650	0.000	4.000	4,495	0.469	0.673	0.000	4.000
Number of children	657	0.426	0.654	0.000	4.000	3,838	0.823	0.894	0.000	6.000	4,495	0.765	0.875	0.000	6.000
Number of elderly	657	0.227	0.447	0.000	2.000	3,838	0.308	0.525	0.000	2.000	4,495	0.297	0.515	0.000	2.000

Source: Authors’ own calculations based on pooled data from three rounds (2011–12, 2015, and 2019) of Bangladesh Integrated Household Survey.
Note: The descriptive statistics of the employment-related variables are blank for non-participants.

Table 3. Estimation results of selection equation by gender.

	Males	Females
	(1)	(2)
Years of education	-0.0042**	0.0086**
	(0.0017)	(0.0034)
Age	0.0084***	0.0225***
	(0.0024)	(0.0033)
Age squared	-0.0001***	-0.0003***
	(0.0000)	(0.0000)
Head of household	0.0091	0.0286*
	(0.0106)	(0.0155)
Married	-0.0058	-0.0422***
	(0.0098)	(0.0138)
Non-Muslims	-0.0041	-0.1288
	(0.0116)	(0.0840)
Sum of non-labor income	-0.0001	-0.0003
	(0.0001)	(0.0003)
Sum of wages of other family members	0.0008	0.0022
	(0.0029)	(0.0028)
Number of wage earners	-0.0088	-0.0256**
	(0.0091)	(0.0115)
Number of children	-0.0068	-0.0201***
	(0.0052)	(0.0069)
Number of elderly	0.0175*	0.0072
	(0.0096)	(0.0171)
Average of all explanatory variables	Yes	Yes
Year fixed effects	Yes	Yes
Observations	4,938	4,495

Note: The coefficients are the marginal effects of the Probit estimation. ∗∗∗, ∗∗, and ∗ indicate significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses represent robust standard errors clustered by household.

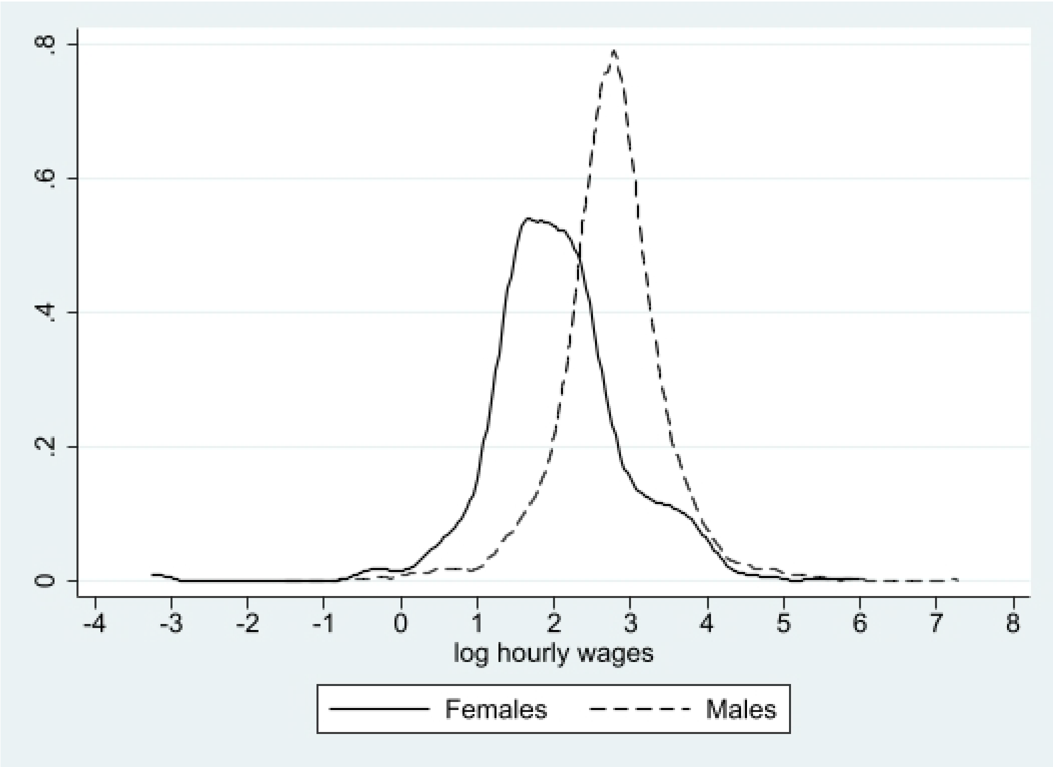
Table 4. Estimation results of wage equation without and with the selectivity correction term by gender.

	Males			Females		
	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.0241***	0.0052	0.0098	0.0773***	0.1104***	0.1075**
	(0.0034)	(0.0082)	(0.0095)	(0.0087)	(0.0418)	(0.0469)
Age	0.0102	0.0132	0.0051	0.0523**	0.0411	0.0329
	(0.0068)	(0.0117)	(0.0152)	(0.0238)	(0.0421)	(0.0736)
Age squared	-0.0001	-0.0002	-0.0001	-0.0006**	-0.0003	-0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0005)	(0.0009)
Head of household	0.0477	0.0863	0.0770	0.0790	-0.0357	-0.0451
	(0.0344)	(0.0603)	(0.0613)	(0.0926)	(0.1719)	(0.1936)
Married	0.1202***	0.1114**	0.1163**	0.0465	0.0786	0.0930
	(0.0372)	(0.0535)	(0.0541)	(0.0906)	(0.1559)	(0.1799)
Non-Muslims	-0.1496***	-0.3483*	-0.3448*	-0.0018	-0.1946***	-0.1624
	(0.0347)	(0.2022)	(0.2055)	(0.0946)	(0.0713)	(0.2979)
Full-time workers	-0.4727***	-0.4602***	-0.4596***	-0.2403***	-0.1917**	-0.1916**
	(0.0212)	(0.0325)	(0.0325)	(0.0733)	(0.0920)	(0.0923)
Non-agricultural workers	0.1185***	0.0362	0.0368	0.1765**	0.2995	0.2980
	(0.0229)	(0.0438)	(0.0439)	(0.0880)	(0.2061)	(0.2030)
Working in urban areas	0.0667*	0.0970**	0.0966**	0.3128**	0.2159	0.2142
	(0.0347)	(0.0489)	(0.0489)	(0.1281)	(0.2328)	(0.2347)
Inverse Mills ratio			-0.4741			-0.0778
			(0.5612)			(0.6590)
Constant	2.4741***	2.6945***	2.8791***	0.6794	-0.1650	0.0945
	(0.1158)	(0.1897)	(0.2898)	(0.4577)	(1.0345)	(2.2102)
Household fixed effects	No	Yes	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Observations	4,820	4,820	4,820	657	657	657
R-squared	0.1620	0.5930	0.5931	0.2590	0.6996	0.6996

Note: ∗∗∗, ∗∗, and ∗ indicate significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses represent robust standard errors clustered by household.

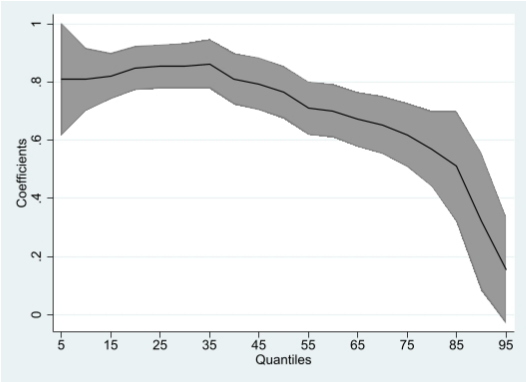
Figure 1. Log-hourly wage distribution by gender.



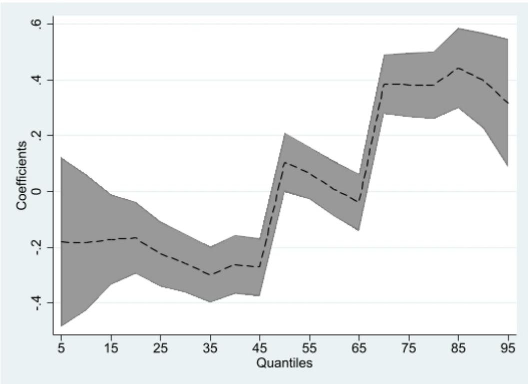
Source: Authors' own calculations based on pooled data from three rounds (2011–12, 2015, and 2019) of Bangladesh Integrated Household Survey.

Figure 2. Overall gender wage gap and its decomposition into the composition and wage structure effects from the 5th to 95th quantiles.

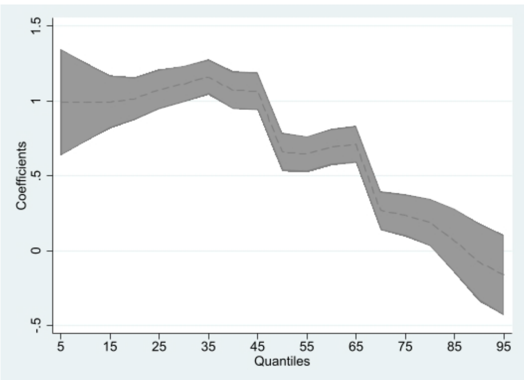
Overall



Composition effect

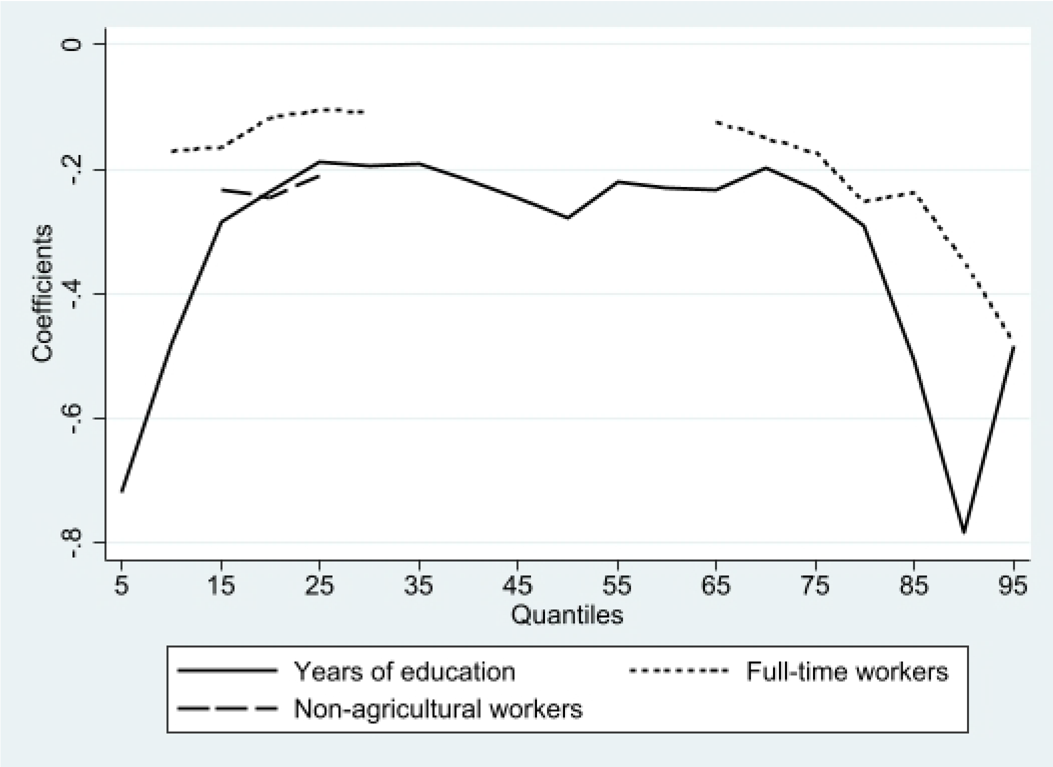


Wage structure effect



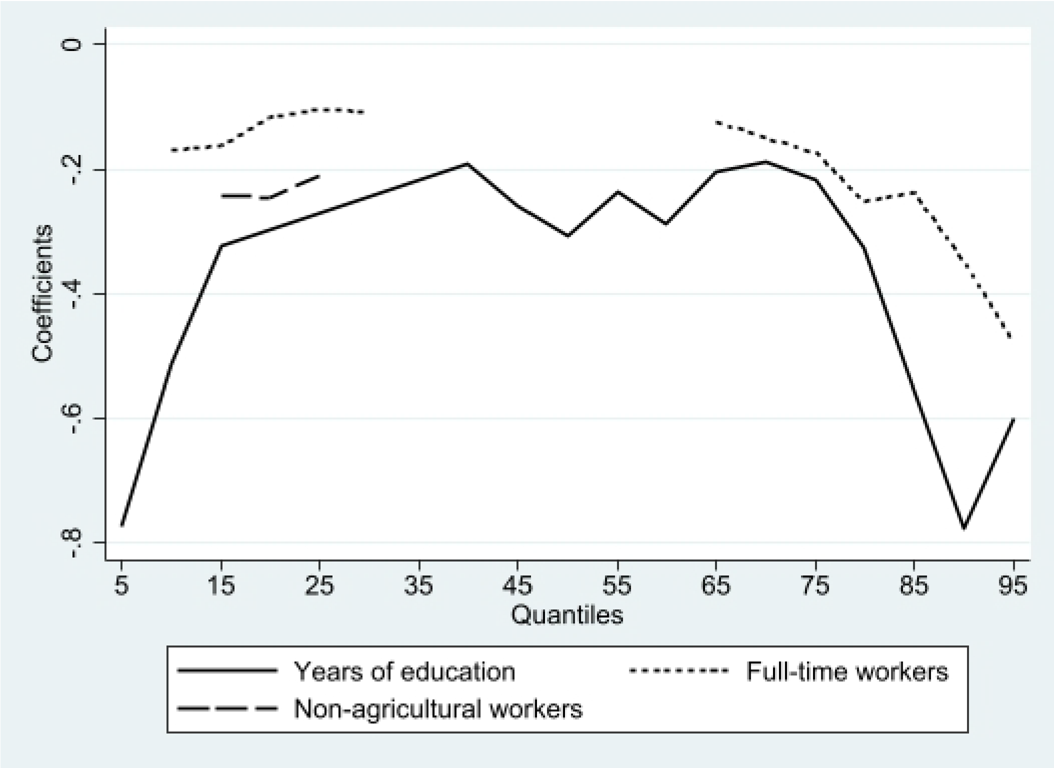
Note: Shaded areas show 95% confidence intervals. The full set of coefficients and standard errors are presented in Table A2 in the Appendix.

Figure 3. Wage structure effects of selected explanatory variables from the 5th to 95th quantiles.



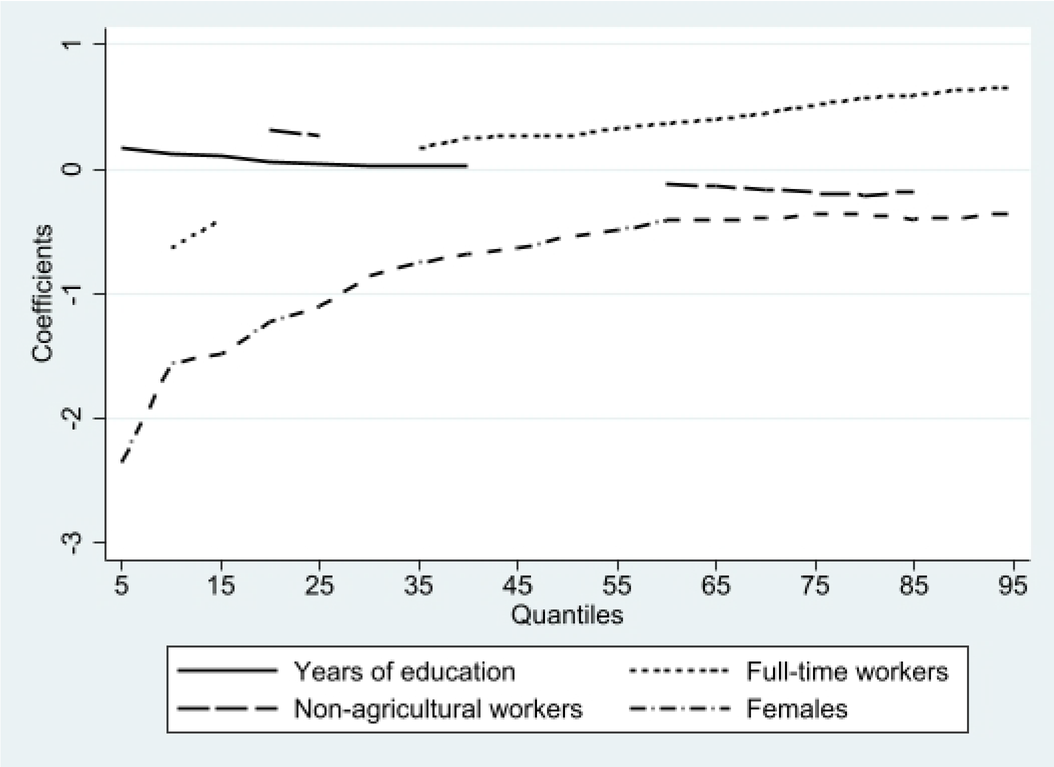
Note: Only coefficients with *p*-values below 0.1 are demonstrated. The full set of coefficients and standard errors are presented in Table A2 in the Appendix.

Figure 4. Wage structure effects of selected explanatory variables from the 5th to 95th quantiles, incorporating the selectivity correction term.



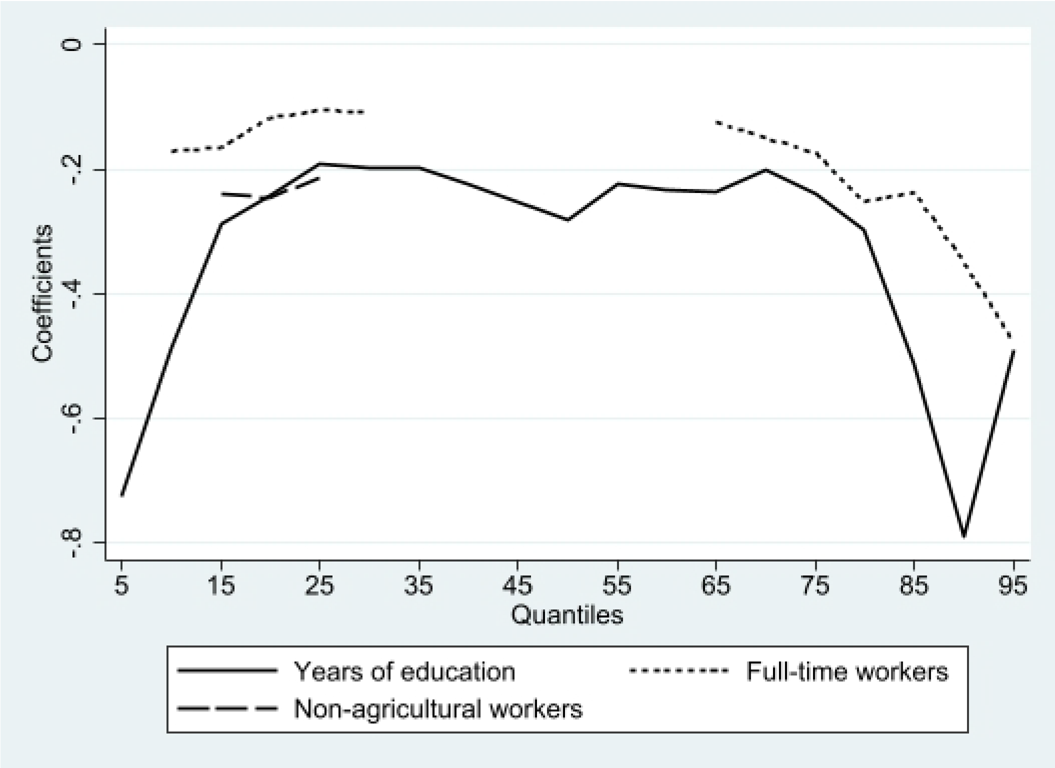
Note: Only coefficients with *p*-values below 0.1 are demonstrated. The full set of coefficients and standard errors are presented in Table A4 in the Appendix.

Figure 5. Estimated coefficients of the interaction terms between female dummy and selected explanatory variables in the pooling sample from the 5th to 95th quantiles.



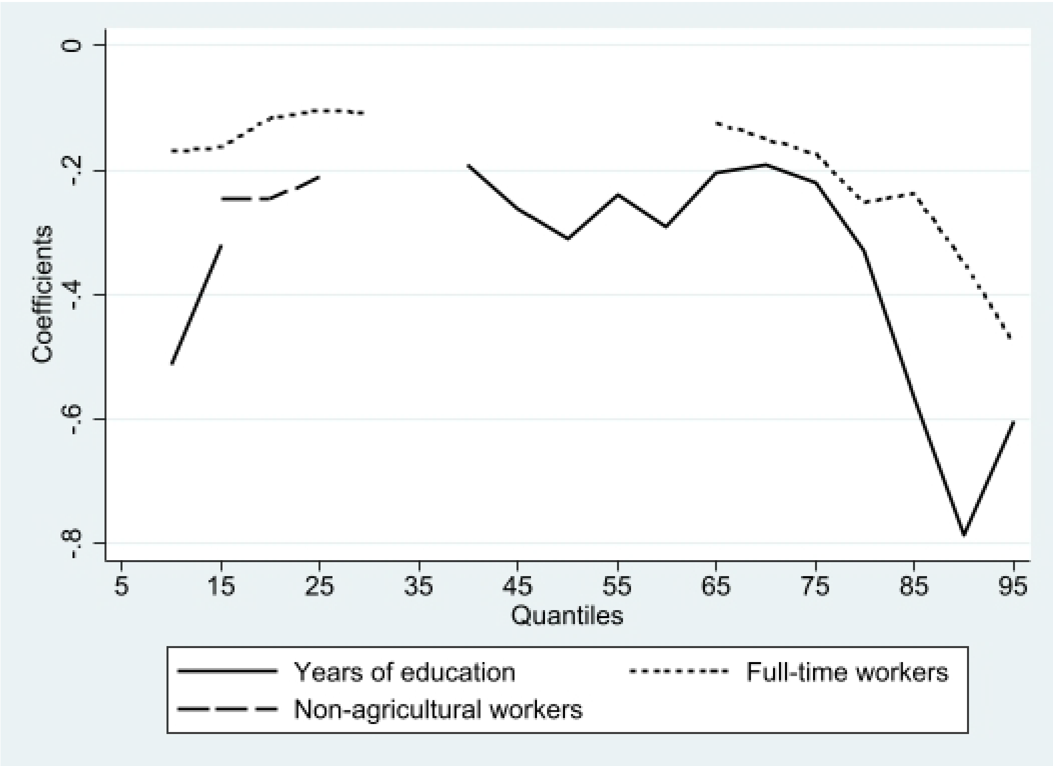
Note: Only coefficients with *p*-values below 0.1 are demonstrated. The full set of coefficients and standard errors are presented in Table A5 in the Appendix.

Figure 6. Wage structure effects of selected explanatory variables from the 5th to 95th quantiles, based on the alternative reference category.



Note: Only coefficients with *p*-values below 0.1 are demonstrated. The full set of coefficients and standard errors are presented in Table A6 in the Appendix.

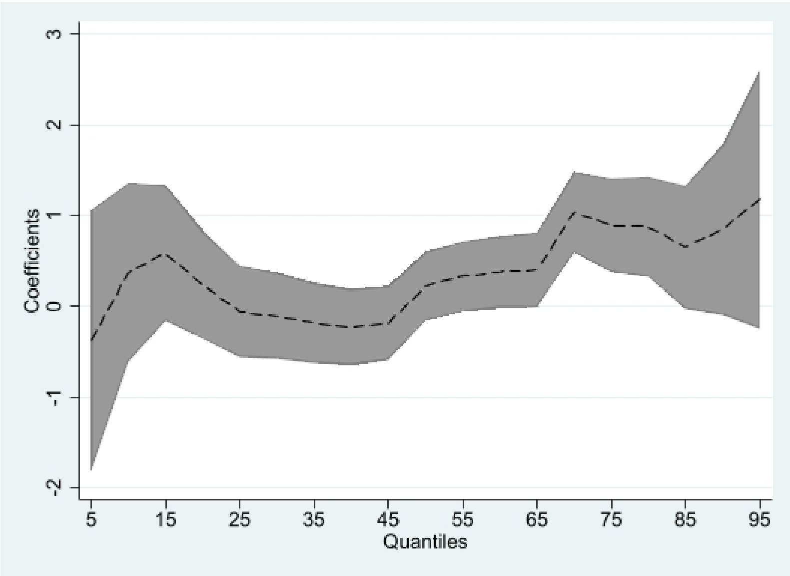
Figure 7. Wage structure effects of selected explanatory variables from the 5th to 95th quantiles, based on the alternative reference category and incorporating the selectivity correction term.



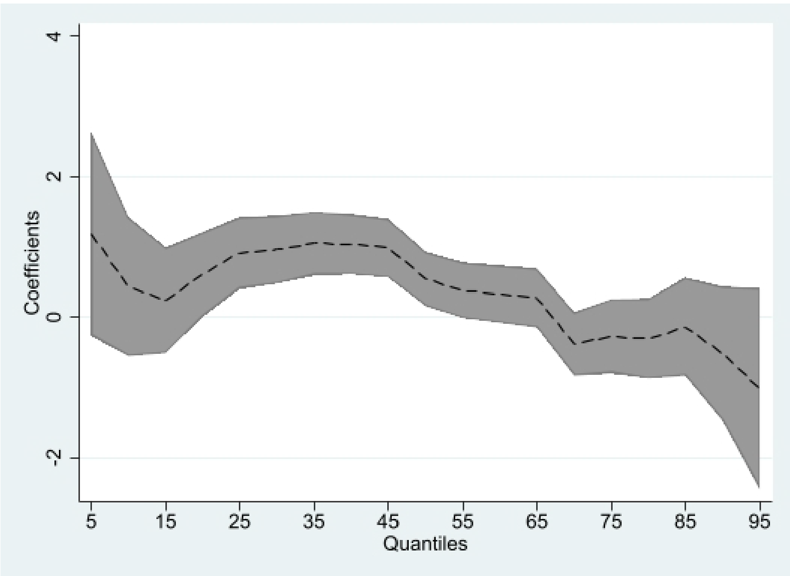
Note: Only coefficients with *p*-values below 0.1 are demonstrated. The full set of coefficients and standard errors are presented in Table A7 in the Appendix.

Figure 8. Decomposition of the overall gender wage gap into the composition and wage structure effects from the 5th to 95th quantiles, including self-employed and unpaid workers in the selection equation.

Composition effect

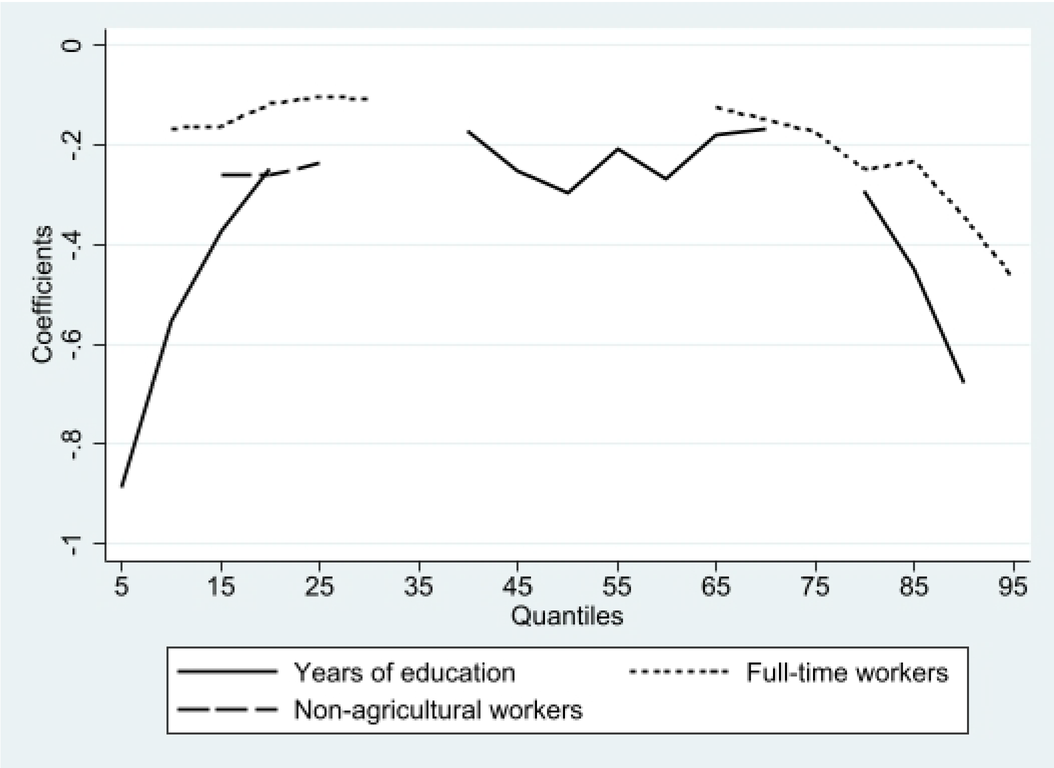


Wage structure effect



Note: Shaded areas show 95% confidence intervals. The full set of coefficients and standard errors are presented in Table A11 in the Appendix.

Figure 9. Wage structure effects of selected explanatory variables from the 5th to 95th quantiles, including self-employed and unpaid workers in the selection equation.



Note: Only coefficients with *p*-values below 0.1 are demonstrated. The full set of coefficients and standard errors are presented in Table A11 in the Appendix.