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Ceilings or floors? A decomposition analysis of the gender pay gap by education in Kenya

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This study investigates gender pay differences in Kenya, emphasizing the role of educational attainment in shaping earnings' disparities. Using data from the Kenya Continuous Household Survey 2021, the analysis employs quantile regression techniques and the *Machado and Mata (2005)* decomposition method to examine earnings gaps across the earnings distribution. Results reveal stark contrasts between low-educated and highly educated women. Low-educated women face substantial pay penalties, particularly in the median quantiles (24.9–66.7%), with evidence of a "sticky floor" effect as they are disproportionately concentrated in low-paying occupations. In contrast, highly educated women experience smaller but persistent gaps (8.3–28.9%), peaking at the top deciles and reflecting a "glass ceiling" effect linked to vertical occupational segregation. Counterfactual decomposition shows that differences in returns to productivity-related characteristics – a proxy for discrimination and unobserved factors – drive the gap for highly educated workers, while low-educated women's penalties stem from occupational segregation and undervalued endowments. Notably, counterfactual scenarios suggest compensating women at male earnings rates would reverse the gap, favoring women across all education levels. The findings underscore the need for targeted policies: addressing horizontal segregation and earnings transparency for low-educated women, and dismantling barriers to high-paying roles for highly educated women.

Keywords: gender pay gap, glass ceiling, sticky floor, highly educated and low-educated, Kenya

For decades, Kenyan women faced societal and informal discrimination that limited their full participation in the labor market. In response, post-2002 governments have implemented a national legal framework to promote gender equality and to empower women. A landmark achievement is the 2010 Constitution of Kenya, which enshrines women's rights as human rights, including dignity and economic, social, and cultural rights *(Republic of Kenya, 2010)*. Complementing this, the Employment Act 2007 prohibits workplace discrimination, while the Employment and Labor Relations Court Act and the Labor Institutions Act ensure gender-neutral labor policies *(Republic of Kenya,* *2010)*. Beyond legal reforms, the Kenyan government has introduced initiatives to enhance equity and women's economic participation. These include the Free Primary Education program implemented in 2003 and the Free Day Secondary Education program in 2008, aimed to improve primary-to-secondary level transition rates to 100% *(Ministry of Education, 2008)*. Additionally, programs like the Women Enterprise Fund-Kenya and the National Government Affirmative Action Fund *(Omanyo, 2021)* were established to empower women and boost their engagement in economic activities.

With these enabling policies, one would expect a decline in labor market inequalities and progressive improvements in the status of African women in the job market. Indeed, analyses of micro-data since the mid-2000s show increased labor market integration for women *(Kenya National Bureau of Statistics [KNBS] Economic Survey*, *various reports)*. However, significant inequities persist. For instance, women in Kenya continue to earn substantially less than men *(UN Women, 2023); Abdiaziz–Kiiru, 2021; Omanyo, 2021)*. Despite the elimination of discriminatory practices and the introduction of Affirmative Action legislation, a substantial share of these pay gaps is attributed to gender earnings discrimination. Alarmingly, this issue has been understudied in the literature, often overshadowed by institutionalized and patriarchal societal norms.

Numerous studies highlight that women face disadvantages in employment prospects, career advancement, and wages, though pay gaps have narrowed in recent decades *(Weichselbaumer–Winter-Ebmer, 2007; Blau–Kahn, 2017; Kolesnikova–Liu, 2011)*. This trend is largely driven by women's increased educational attainment, work experience, and occupational choices, which significantly shape the gender pay gap over time. However, when controlling for gender differences in observable characteristics, the pay gap has remained relatively stable. According to the *European Commission (2005),* education is the most significant observable factor explaining wage inequality between men and women. As educational levels rise for both sexes, men and women increasingly occupy similar roles, reducing the pay gap. Ultimately, the female-male earnings gap is strongly influenced by occupation type and, critically, by education level. Specifically, highly, and low-educated individuals possess distinct skills and competencies, leading them to different occupations. Consequently, educational attainment shapes the jobs workers can access, the income they earn, and the extent of gender earnings differentials.

Recent studies on gender pay differentials by education, focusing on differences in productive characteristics and their rewards, reveal distinct patterns across education levels. For highly educated workers, *De la Rica et al. (2008)* found that the wage gap widens at higher distribution percentiles, consistent with the glass ceiling hypothesis. In contrast, the gap narrows for less-educated workers. In Italy, *Addabbo and Favaro (2011)* found that for low-educated workers, the wage gap is primarily driven by differences in rewards, particularly at the upper end of the distribution. Highly educated women, however, possess better characteristics than their male counterparts, partially mitigating the wage gap. *Mussida and Picchio (2014)* further noted that low-educated women face larger wage penalties, especially at the lower end of the distribution. In South Africa, *Padayachie (2015)* identified a clear glass ceiling for highly educated women and a sticky floor effect for low-educated workers.

This paper builds on the existing literature by examining gender pay gaps in Kenya in relation to educational endowments. It aligns with the framework of vertical earnings differences between highly educated and low-educated workers, suggesting that workers with varying education levels occupy roles requiring distinct competencies. These roles are complementary in production but unevenly influenced by labor market factors. To the author's knowledge, no prior empirical study in Kenya has broken down the gender wage gap by education. Addressing this gap, the study contributes to the debate by applying quantile regression to estimate individual covariates across the earnings distribution and using the *Machado and Mata (2005)* procedure to derive both observed and counterfactual pay gaps, adjusted for sample selection. Previous studies emphasize that in countries like Kenya, where gender gaps in employment rates are significant, accounting for gender differences in workforce participation is critical *(Olivetti–Petrongolo, 2008; Picchio–Mussida, 2011)*. Using this decomposition technique, the gender pay gap at each decile is split into components attributable to differences in characteristics and differences in returns to endowments. This allows us to examine whether a „glass ceiling"[1] or „sticky floor"[2] effect is more prevalent in the Kenyan labor market. Thus, the primary objective of present study is to determine whether the dichotomy between highly educated and low-educated workers reflects distinct patterns of gender pay gaps, as hypothesized.

The rest of the paper is structured as follows. Section 1 provides a review of the Education system and Reforms in Kenya as well as the review of related literature. Section 2 discusses the Empirical strategy: methods while Section 3 presents Data Concepts. Section 4 presents the descriptive statistics. Section 5 presents the main results while Section 6 discusses the results. Section 7 draws conclusions and policy implications.

[1] Glass ceiling is a situation where the gender gaps are typically wider at the top of the wage distribution.
[2] A sticky floor is a situation whereby the gender gaps are wider at the bottom of the wage distribution.

1. Literature review

1.1 Education system and reforms in Kenya

In the colonial Kenya (1895–1963), the education system was structured along racial lines, stratified into three groups: Europeans, Asians, and Africans. Africans received inferior education focused on manual labor to serve the needs of the white and Asian populations. Asians were educated for middle-level occupations, such as artisanship, trade, and vocational roles. Europeans, however, were provided with a specialized education system designed to cultivate leadership. This segregative system hindered unity among the racial groups. In view of this, the Phelps-Stokes Commission (1924–1925) recommended establishing vocational post-primary institutions nationwide to equip Africans with practical skills *(UNESCO, 2005; Muricho, 2023).*

After independence in 1963, the Kenyan government initiated educational reforms to align the system with the physical, political, social, and economic needs of the newly independent state. Several education commissions were established to reshape the system, including the Ominde Report-1964, Bessey Report-1972, Gachathi Report-1976, Mackay Report-1981, Kamunge Report-1988, and Koech Report-1999 *(Muricho, 2023)*. These reforms aimed to support nation-building and were consistent with the recommendations of the Addis Ababa Conference, which advocated for a suitable curriculum in primary and secondary schools across African countries. The *Ominde Commission (1964),* in particular, recommended revising the colonial curriculum to make it more relevant to Kenyan learners. It proposed the introduction of the 7-4-2-3 system, modeled on the British system, and emphasized education's role in national development. Notably, abolished the racial segregation enforced by the colonial government *(Kaplun, 2019; Mckov, 2022)*.

In 1972, the Kenyan government appointed the Bessey Commission to review the curriculum policy. The Bessey Report found that the post-independence curriculum failed to meet national educational goals, as emphasized memorization over vocational and technical skills in secondary schools. This led to recommendations for structural changes and the inclusion of additional subjects, paving the way for the Gachathi Education Commission (1976). The Gachathi Commission addressed rising unemployment among school leavers and proposed restructuring the curriculum to expand Science, Mathematics, technical and vocational subjects *(Momanyi–Rop, 2020)*. The Mackay Report (1981) recommended extending primary education from seven to eight years, transitioning the system from the 7-4-2-3 to the 8-4-4 structure *(Muchunguh,* *2021)*. These changes introduced technical and vocational subjects in primary schools. In January 1985, comprehensive education reforms were implemented, including the extension of primary schooling to eight years. This shift was driven by the recognition that primary education was often the terminal stage for many students, necessitating a longer, practical-oriented curriculum to equip them with marketable skills for the job market *(Muchunguh, 2021)*.

Since 1985, Kenya's public education has operated under the 8-4-4 system, comprising 8 years of primary education, 4 years of secondary school, and 4 years of university *(Muricho–Chang'ach, 2013)*. However, this system has been criticized for perpetuating social and economic hierarchies, systematically excluding children from lower-income backgrounds from prestigious secondary schools. Moreover, the performance gap between private and public schools widened, with private schools dominating enrollment in high-performing institutions. Consequently, students from private academies often secure better courses at public and private universities *(Amutabi, 2019)*. In response to these challenges, the basic education curriculum underwent further reform. The Douglas Odhiambo Taskforce (2012) proposed the Competency-Based Curriculum (2-6-6-3), which has been under implementation since 2017. This system includes 2 years of pre-primary education, 6 years of primary education (Grades 1–6), 3 years of junior secondary (Grades 7–9), 3 years of senior secondary (Grades 10–12), and 3 years of university education (tertiary education).

A significant achievement in Kenya is the remarkable increase in girls' access to primary education. However, at the secondary level, the gross enrollment rate for males exceeds that of females, though the female net enrollment rate has surpassed males since 2010 *(KIPPRA, 2013)*. According to *Muricho (2023),* Kenya made substantial progress toward gender parity in primary education enrollment and near parity at the secondary level. A key driver of this progress is the implementation of Free Primary Education (FPE) in 2003 and Free Day Secondary Education, aimed at ensuring equity and a 100% transition rate from primary to secondary education *(Ministry of Education, 2008)*. As a result, the transition rate rose from 83.3% in 2018 to 95% by early 2020 *(KNBS, Economic Survey, 2021)*.

Affirmative actions and gender mainstreaming in education led to increased female enrollment at primary, secondary, university levels, and Technical and Vocational Education and Training [TVET] institutions. Additionally, more women are enrolling in STEM courses (Commission for University Education [CUE], 2018). Despite these advancements, challenges persist, including school dropouts due to unintended pregnancies, child marriages, and socio-cultural practices like Female Genital Mutilation [FGM], children assuming household and parental responsibilities in the absence of parents, weak coordination between national and county governments in education provision, and emerging issues such as betting and gambling, Covid-19, and cyberspace.

According to the *KNBS Economic Survey (2022)*, total primary school enrollment increased by 1.1%, from 10,170.1 thousand in 2020 to 10,285.1 thousand in 2021. Girls' enrollment rose by 1.3% to 5,041.7 thousand, while boys' enrollment increased by 1.0% to 5,243.5 thousand during the same period (see Figure A1 in Appendix). At the secondary level, enrollment has also grown steadily, with girls slightly surpassing boys since 2019. At the tertiary level, university enrollment is growing slowly, while enrollment in Technical and Vocational Education and Training (TVET) has surged (see Figure A2 in Appendix). Additionally, Kenya's literacy rate for individuals aged 15 and above has increased from 72% in 2007 to 82.62% in 2021, significantly exceeding the sub-Saharan Africa average of 65%.

1.2 Empirical studies

Research on gender pay differentials advanced significantly over the past few decades, building on the foundational Oaxaca-Blinder approach *(Blinder, 1973; Oaxaca, 1973)*. This early work established a critical distinction between two components of the pay gap: one due to gender differences in productive characteristics and the other due to differences in the rewards associated with those characteristics. Subsequent contributions, such as those by *Machado and Mata (2005)* and *Firpo et al. (2009, 2018),* emphasized the importance of analyzing gender pay gaps across the entire wage distribution, moving beyond the earlier focus on average values.

Mussida and Picchio (2014) analyzed the gender wage gap by educational attainment in Italy using data from the ECHP from 1994 to 2001. They estimated wage distributions while accounting for covariates and sample selection, separately examining highly educated and low-educated men and women. Using a decomposition approach, they isolated the portion of the wage gap attributable to differences in remuneration for similar characteristics across the entire wage distribution. Their findings revealed significant wage penalties for women, particularly in the case of those with lower education. These penalties were more pronounced after controlling for sample selection bias from unobservable factors, especially at the lower end of the wage distribution.

De la Rica et al., (2008) investigated the gender wage gap by education across the wage distribution in Spain using data from the ECHP. They employed quantile regression and panel data techniques to estimate wage regressions. Unlike the steeply increasing gender gap trends observed in other countries, Spain's flatter trend reveals a notable compositional effect. For highly educated workers, the gap widens at higher percentiles, aligning with the traditional glass ceiling hypothesis. In contrast, for less-educated workers, the gap narrows, a phenomenon they termed the „floor pattern." They attributed this pattern to statistical discrimination by employers, particularly in contexts where less-educated women have low labor force participation rates.

Addabbo and Favaro (2011) analyzed wage differentials in Italy by integrating gender and education perspectives. The study aimed to determine whether the gender pay gap differs between highly educated and low-educated workers and to assess how gender differences in characteristics and market rewards influence these groups. Using data from the European Community Household Panel (ECHP), the authors applied quantile regression analysis and an adaptation of the *Machado and Mata (2005)* procedure to evaluate the predicted wage gap across the female wage distribution. The findings revealed significant differences in the extent and trends of the predicted gap across educational levels. For low-educated workers, the gap was primarily driven by differences in rewards, with lower education or experience contributing to disparities, especially at the higher end of the distribution. In contrast, highly educated women exhibited better characteristics than their male counterparts, which partially offset the wage gap.

Machin and Puhani (2003) observed that male college graduates in Europe typically earned higher wages than female graduates, with differences in college majors explaining a substantial portion of the wage gap. In a related study, *Dolado et al. (2003)* showed that younger, more educated women had higher labor market participation rates compared to older, less educated women. Together, these studies highlight the critical role of education and training in reducing gender wage disparities and advancing gender equality in the global labor market.

In South Africa, *Padayachie (2015)* examined education and gender pay inequality using Wave I (2008) of the National Income Dynamics Study. Applying the *Machado and Mata (2005)* quantile decomposition method, the study found that on average men earned higher hourly wages than women. Interestingly, women invested more in their human capital, particularly in post-secondary degrees, contradicting predictions from human capital theory. Gender pay disparities were relatively small at the center of the earnings distribution for both low and highly educated workers. However, the study identified a glass ceiling for highly educated women and a sticky floor effect for low-educated workers. While women exhibited better observable labor market characteristics across the wage distribution and education levels, men earned more in the upper and middle quantiles for highly and low-educated workers.

This literature review examines the evolution of Kenya's education system and its impact on gender disparities, alongside global empirical studies on gender wage gaps. In colonial Kenya, the education system was racially segregated, with Africans receiving inferior education focused on manual labor, while Europeans and Asians were prepared for leadership and middle-level roles. Post-independence reforms aimed to align education with national development goals, leading to the introduction of systems like 7-4-2-3 and later 8-4-4, which emphasized vocational training and extended primary education. Despite progress, the 8-4-4 system has been criticized for perpetuating social and economic hierarchies, prompting further reforms such as the Competency-Based Curriculum (2-6-6-3). Affirmative actions and policies like Free Primary Education (FPE) have significantly increased female enrollment, yet challenges like school dropouts due to socio-cultural practices and economic barriers persist. Empirical studies on gender wage gaps, such as those by *Mussida and Picchio (2014)* and *De la Rica et al. (2008),* highlight the role of education in shaping wage disparities, with findings indicating that highly educated women often face a „glass ceiling," while low-educated women experience a „sticky floor effect." These studies underscore the importance of education and training in reducing gender wage gaps and advancing gender equality globally.

2. Empirical strategy

2.1 Machado and Mata decomposition method

The Oaxaca-Blinder decomposition technique and its variants are widely used to analyze factors behind average earnings differences between men and women. This method splits the gender pay gap into two parts: one explained by differences in productivity-related characteristics and another unexplained, attributed to differences in returns to these characteristics *(Blinder, 1973; Oaxaca, 1973)*. However, studies reveal that the gender pay gap varies across the earnings distribution *(Albrecht et al., 2003; Arulampalam et al., 2007; De la Rica et al., 2008)*. To address this, *Machado and Mata (2005)* introduced a method combining quantile regression and bootstrap techniques, enabling the analysis of counterfactual density functions *(Heinze, 2010)* and offering a more detailed understanding of pay disparities.

The quantile regression method, introduced by *Koenker and Bassett (1978),* provides estimates for various quantiles, enabling analysis beyond conditional means and without assuming normality. Unlike ordinary least squares (OLS), focusing on conditional means, quantile regression uses a linear model to estimate conditional quantiles, including quantiles of the response variable's distribution. This makes quantile regression particularly useful for analyzing skewed distributions, such as those found in wage or income inequality studies *(Koenker–Hallock, 2001)*. While OLS examines mean effects, where covariates act as shift factors, quantile regression allows for the examination of marginal effects of covariates on the dependent variable at different points across the distribution, not just at the mean.

Let lnW_{ij} denote the log wage of worker i working in form j, X_i is a vector of individual characteristics, and Z_i denotes firm/industry characteristics. The model specifies the θth quantile of the conditional distribution of lnW_{ij} given X_{ij} and Z_{ij} is a linear function of these covariates, along with a binary gender indicator g_{ij} $(for\ males\ g = m\ and\ for\ females\ g = f)$. The model is expressed as:

$$Q_\theta\left(lnW_ij \middle| g_{ij}, X_i, Z_i\right) = g_{ij}\alpha_\theta + X_i\beta_\theta + Z_i\delta_\theta + \mu_{\theta ij}, \qquad \theta \in (0,1) \tag{1}$$

Following *Koenker and Bassett (1978),* Equation (1) can be rewritten as:

$$lnW_{ij} = g_{ij}\alpha_\theta + X_i\beta_\theta + Z_i\delta_\theta + \mu_{\theta ij} \quad for\ g = m, f; i = 1,2, \dots\dots, N; j = 1,2, \dots\dots, M \tag{2}$$

Here $\mu_{\theta ij}$ satisfies $Q_\theta\left(lnW_ij \middle| g_{ij}, X_i, Z_i\right) = 0$. The α_θ represents the gender pay gap at the θth quantile, adjusted for productivity-related characteristics. Equation (2) assumes that men and women receive equal rewards for their characteristics.

To assess whether the returns to characteristics differ by gender, Equation (2) can be estimated separately for males and females:

$$lnW_{ij} = X_{ij,g}\beta_g(\theta) + Z_{ij,g}\delta_g(\theta) + \mu_{\theta ij,g} \quad for\ g = m, f; i = 1,2, \dots\dots, N_g; j = 1,2, \dots\dots, M \tag{3}$$

where $q_{\theta,g}\left(\mu_{\theta ij,g} \middle| X_{ij,g}, Z_{ij,g}\right) = 0$ and the quantile regression coefficient vectors $\beta_g(\theta)$ and $\delta_g(\theta)$ are estimated using the optimization[3] framework proposed by *Koenker and Bassett (1978)*. Specifically, they are obtained by solving the following minimization problem:

$$\begin{bmatrix}\hat\beta(\theta)\\ \hat\delta(\theta)\end{bmatrix} = \underset{\beta_g(\theta), \delta_g(\theta)}{Min} \Big[\textstyle\sum_{i.lnw_{ij,g} \geq X_{ij,g}\beta_g(\theta) + Z_{ij,g}\delta_g(\theta)} \theta \,|\, lnW_{ij,g} - X_{ij,g}\beta_g(\theta) - Z_{ij,g}\delta_g(\theta)| + \sum_{i.lnW_{ij,g} < X_{ij,g}\beta_g(\theta) + Z_{ij,g}\delta_g(\theta)} (1-\theta) \,|\, lnW_{ij,g} - X_{ij,g}\beta_g(\theta) - Z_{ij,g}\delta_g(\theta)| \Big] \tag{4}$$

The estimated coefficients from quantile regression, denoted as $\hat\beta(\theta)$[4] and $\hat\delta(\theta)$, can be used to decompose differences in the log hourly wage distributions of men and women at various quantiles. Building on the foundational work of *Blinder (1973)* and *Oaxaca (1973)*, the gap in average earnings between genders can be decomposed into two components: (1) differences in personal characteristics and

[3] Consistency and asymptotic normality of the estimators can be proved if the minimization problem (2) is transferred into a GMM framework (see e.g., *Buchinsky, 1998*). The asymptotic covariance matrix of the estimator can also be derived from this model framework.

[4] We estimate the vector of coefficients $\hat\beta(\theta)$simultaneously, by means of the bootstrapping procedure that makes possible to test whether coefficients of different quantile regressions are significantly different pair-on-pair.

(2) differences in coefficients (often interpreted as the unexplained or price differential). While the Blinder-Oaxaca decomposition focuses on differences at the mean of the wage distributions, *Garcia et al. (2001)* extended this approach by integrating it with quantile regression to analyze the rent component at different points in the wage distribution. However, a limitation of this method is the fact that only considers the mean of the covariate distributions, ignoring variations in higher moments. As a result, we do not employ this specific technique in our analysis.

Machado and Mata (2005) introduced a decomposition method that integrates quantile regression with a bootstrap approach to simulate counterfactual wage distributions. This method allows for the analysis of differences in higher moments of the independent variables' distributions. The first step involves estimating the conditional quantiles of the dependent variable y using quantile regression, as specified in Equation (1). The second key concept relies on the probability integral transformation theorem: if U is uniformly distributed on $[0, 1]$, then $F^{-1}(U)$ follows distribution F. Thus, for a given X_i and a random $\theta \sim U[0,1]$, $X_i\beta_0$ has the same distribution as $y_i|X_i$. If X_i is randomly drawn from the population, $X\beta_0$ matches the distribution of y. Building on *Albrecht et al. (2003)* and the Machado–Mata decomposition, the procedure to decompose the gender wage gap at the θth quantile involves the following four steps:

1. Draw a random sample of size n from a uniform distribution $U[0,1]$: $\theta_1, \theta_2, \dots\dots\dots.., \theta_n$.
2. For each θ in step (1), estimate quantile regression coefficients for male and female employees separately: $\begin{bmatrix} \hat{\beta}_m(\theta) \\ \hat{\delta}_m(\theta) \end{bmatrix}, \begin{bmatrix} \hat{\beta}_f(\theta) \\ \hat{\delta}_f(\theta) \end{bmatrix}$; $\theta = 0.01, \dots\dots.0.99$. This yields 99 sets of coefficients for males and 99 for females.
3. Simulate earnings distributions: For males and females separately, generate a random sample of size n (with replacement) from a set of covariates $[X, Z]$. Using the estimated coefficients $(\hat{\beta}_g\theta, \hat{\delta}_g\theta)$, construct three sets of predicted earnings: (i) simulated female log earnings distribution $\{\tilde{X}_f, \tilde{Z}_f\} = X_f\hat{\beta}_f(\theta), Z_f\hat{\delta}_f(\theta)$, (ii) simulated male log earnings distribution $\{\tilde{X}_m, \tilde{Z}_m\} = X_m\hat{\beta}_m(\theta), Z_m\hat{\delta}_m(\theta)$, and (iii) the counterfactual distribution $\{\tilde{X}_f, \tilde{Z}_m\} = X_f\hat{\beta}_m(\theta), Z_f\hat{\delta}_m(\theta)$. This represents the log earnings distribution females would have if they retained their own characteristics but were paid like men.[5]

[5] In this procedure, the marginal distributions of male and female log hourly wage, $X_m\hat{\beta}_m(\theta), Z_m\hat{\delta}_m(\theta)$, $X_f\hat{\beta}_f(\theta), Z_f\hat{\delta}_f(\theta)$ are generated using the same procedure to generate the counterfactual marginal distribution $X_f\hat{\beta}_m(\theta), Z_f\hat{\delta}_m(\theta)$ (see *Arulampalam et al., 2007* for a similar approach). An alternative to this approach would be to use the empirical log hourly wage distributions of males and females in comparisons (see, for example *De la Rica et al., 2008*).

4. Decompose the gender pay gap. Finally, decompose the difference between the θth quantile of the male and female wage distributions into two components[6]:

$$X_m\hat{\beta}_m(\theta) - X_f\hat{\beta}_f(\theta) = (X_m - X_f)\hat{\beta}_m(\theta) + X_f\left(\hat{\beta}_m(\theta) - \hat{\beta}_f(\theta)\right) + residual \quad (5)$$

The first term captures differences due to characteristics, while the second term represents differences due to returns to those characteristics (the unexplained or price differential). The residual term in the decomposition comprises three types of error: simulation errors, sampling errors, and specification errors arising from the linear quantile regression model. In this paper, we assume the linear quantile regression model is correctly specified. As a result, as the number of simulations and observations increases, the residual term will asymptotically approach zero. This implies that Equation (5) provides a valid decomposition of the differences in quantiles between the male and female wage distributions into two components: the coefficient effect (differences in returns to characteristics) and the covariate effect (differences in characteristics themselves).

3. Data concepts

Present study utilizes data from the 2021 *Kenya Continuous Household Survey (KCHS)*, conducted by the Kenya National Bureau of Statistics (KNBS). The survey encompassed 17,042 households and 68,677 individuals. Consistent with pay gap analyses, the sample is restricted to employed individuals with an income, aged 15 to 65, reflecting Kenya's working-age range and mandatory retirement age *(Republic of Kenya, 2010; Omanyo, 2021)*. Self-employed individuals, small-scale farmers, full-time students, and military personnel were excluded due to incomparable earnings and hours worked data. After these exclusions, the final sample consists of 6,653 employees, including 4,210 males and 2,443 females aged 15 to 65.

[6] The decomposition of differences in wage distributions is applied using the Stata command rqdeco (see *Melly, 2006*). *Melly (2006)* shows that this procedure is numerically identical to the *Machado–Mata (2005)* decomposition method when the number of simulations used in Machado and Mata procedure goes to infinity. In the decomposition procedure of our study, rather than taking n random draws from (0,1) and estimating n quantile regression coefficients, the decomposition is performed for the 99 percentile differences in wages between men and women. The standard errors for the counterfactual densities are obtained by repeating the procedure 100 times.

The estimated models include the Mincer earnings equation, where the logarithm of the wage rate[7] (gross monthly earnings) is explained by individual productive characteristics, such as education and potential experience.[8] Additionally, the models incorporate demand-side labor market variables, including firm size, sector of employment, and industry, as well as demographic factors like marital status and residence, all of which influence wage levels. This empirical approach aligns with earnings functions used in recent studies across various countries *(Arulampalam et al., 2007; De la Rica et al., 2008; Addabbo–Favaro, 2011; Mussida–Picchio, 2014)* and in Kenya *(Agesa et al., 2009, 2013; Abdiaziz–Kiiru, 2021; Omanyo, 2021)*. Unlike previous surveys, the KCHS dataset provides detailed information on occupational content, allowing individuals to be categorized into distinct occupational groups. This approach replaces the use of occupation dummy variables, which can influence wage rates significantly. Controlling for occupational categories is particularly critical, as occupational segregation – where women are concentrated in certain jobs – has been shown to explain a substantial portion of the gender pay gap *(Bayard et al., 2003; Orraca et al., 2016; Ismail et al., 2017)*.

Determining the appropriate categorization of the sample, particularly the educational threshold for delineating subsamples is a key preliminary step in analyzing wage gaps by educational levels. While studies often differentiate between workers with a university degree and those with lower educational levels – especially when examining the impact of globalization, trade, and migration on wage disparities – the author adopt a different approach. This analysis separates workers with compulsory basic education from those with higher-level education, using the threshold of compulsory basic education in Kenya *(Kaplun, 2019; Mckov, 2022; Muchunguh, 2021; Muricho–Chang'ach, 2013)*. In Kenya's education system, low-educated individuals (compulsory basic education) are defined as those who have completed primary, post-primary or secondary education. Highly educated individuals (higher education) are those with a higher college diploma, bachelor's degree or postgraduate education. This categorization is chosen because it better reflects the structure of Kenya's educational system and the corresponding occupational opportunities available to workers at different educational levels.

Given these considerations, workers with compulsory basic education are classified as low-educated and those with at least a post-compulsory school

[7] The authors used in this analysis monthly earnings as by multiplying the weekly hours by 4.3, the monthly hours of work for women, and hence, unbiased hourly earnings have been overestimated. For the purposes of this study, the term "wages" refers to gross monthly earnings from waged employment, covering wages, salaries, and other earnings, including allowances, received in the past month.

[8] Potential experience is calculated as Age minus 6 pre-schooling years minus years in school (Age-6-S).

diploma as highly educated. According to the International Standard Classification of Education (ISCED), this corresponds to distinguishing between ISCED levels 0–2 and 3–7 *(Addabbo–Favaro, 2011)*. Using this framework, the KCHS dataset enables us to create a dummy variable identifying individuals with a completed university degree (ISCED 5–7), which is included in the estimates for the highly educated group. Following this categorization, our sample comprises 1,500 highly educated workers and 5,153 low-educated workers.

4. Descriptive statistics

4.1 Gender disparities by education

Table 1 presents descriptive statistics on the educational characteristics of employed workers, disaggregated by gender, employment sector, and age cohorts. The results indicate that women generally have a higher distribution[9] of education at advanced levels, suggesting educational parity and even surpassing men in educational attainment across Kenya's educational hierarchy. While slightly more men than women have completed basic education (primary, post-primary, and secondary), overall, gender equality in education is evident among employed workers. Notably, a gender gap favoring men with bachelor's degrees persists across all age groups but diminishes among older cohorts. Among younger age groups, the largest education gap is observed for those with diplomas. However, this gap narrows as educational levels increase across all age cohorts.

[9] Primary education includes standard 1–8 (grade 1–8); Secondary education entails form 1–4 (grades 9–12); Diploma includes certificate or diploma course (1–3 years) and Higher national diploma course; Bachelors entails undergraduate studies (1–6 years); post-graduate includes masters' degree (1–2 years) and PhD studies (1–3 years). Post-primary education includes adult basic and secondary education, vocational training (1–2 years).

Table 1

Distribution of workers by gender and education

(%)

Denomination	Primary		Post-primary		Secondary	
	men	women	men	women	men	women
All waged employees	41.09	39.00	1.85	1.40	37.82	27.03
Employment sector						
Public sector	5.54	10.56	0.58	1.43	14.58	29.21
Private formal	9.78	18.70	3.79	0.70	22.11	40.45
Private informal	58.88	51.73	1.01	2.19	32.64	38.83
Age cohorts						
15–24 years	33.31	38.88	2.93	2.44	42.39	51.31
25–34 years	35.64	34.35	0.97	1.92	26.23	39.73
35+ years	44.50	47.07	1.14	1.60	21.64	31.86
	Diploma		Bachelors		Post-graduate	
	men	women	men	women	men	women
All waged employees	11.76	21.62	6.45	8.50	1.03	2.22
Employment sector						
Public sector	49.37	28.16	24.66	27.10	5.28	3.54
Private formal	41.24	23.90	16.69	12.75	6.39	3.49
Private informal	6.72	6.02	0.72	1.21	0.03	0.02
Age cohorts						
15–24 years	16.53	6.25	4.74	1.12	0.09	0.00
25–34 years	24.50	15.64	10.66	7.99	1.99	0.38
35+ years	21.26	10.57	8.20	7.01	3.25	1.88

Note: individuals aged 15 and above. Weighted data.
Source: author's calculations based on *KCHS (2021)* data.

Both men and women with higher education levels are more likely to hold better-paid jobs. In the public sector, employment is primarily composed of workers with secondary education or higher. In the private sector, a clear divide exists between the formal and informal segments: the formal sector is dominated by workers with secondary education and above, while the informal sector consists mainly of those with secondary education or below, for both genders. Additionally, the private formal and public sectors show a slightly higher proportion of highly educated men compared to women, suggesting that women face greater competition or barriers in accessing private formal employment. This disparity may stem from factors such as gender biases, occupational segregation, or limited opportunities for women to enter and advance in certain industries or roles within the private formal sector. Overall, a slightly higher proportion of employed workers have attained compulsory basic education.[10]

[10] For the purposes of this study, compulsory basic education includes primary, post-primary, and secondary education, while higher education encompasses college/diploma, bachelor's, and post-graduate education.

The educational structure creates a stark divide in the labor market, separating those with compulsory education from those with higher qualifications. As illustrated in Table 2, low-educated individuals are predominantly confined to low-skilled operative and blue-collar jobs, while highly educated individuals have access to professional roles. Approximately 61% of highly educated women work as professionals, compared to around 44% of highly educated men. In contrast, low-educated individuals are significantly underrepresented in top occupations, with only 4.5% of women and about 3% of men employed as professionals.

Table 2

Type of occupation in primary job: distribution by education and gender

(%)

Denomination	Highly educated		Low educated	
	men	women	men	women
Legislators, administrators, and managers	5.1	4.0	1.3	0.98
Professionals	43.9	60.4	3.2	4.5
Technicians and associate professionals	1.3	5.9	0.5	1.2
Secretarial and clerical services	15.6	15.1	14.2	19.0
Service workers and market sales workers	4.2	2.9	24.7	37.7
Agriculture, forestry, and fishery workers	2.6	3.4	15.2	28.9
Craft and trade related workers	11.1	5.7	2.7	1.3
Plant and machine operators and assemblers	9.2	1.7	23.8	4.6
Elementary occupations	7.0	1.0	14.4	1.9

Note: individuals aged 15 and 65 years.
Source: author's calculations based on *KCHS (2021)* data.

4.2 The raw earnings difference by education levels

Table 3 presents raw statistics on the gender earnings difference. On average, both low-educated and highly educated women earn less than their male counterparts. The average raw earnings difference is 42.4% for low-educated women and 12.3% for highly educated women, indicating that the gap is more pronounced among low-educated workers. However, the pattern of the raw gender pay gap across the earnings distribution varies by education level. For low-educated workers, the gender pay gap follows a U-shaped pattern: it is highest at the bottom of the distribution (66.7% at the 10th percentile), lowest at the 25th percentile (approximately 25%) and rises again at the top (62.5% at the 75th percentile). In contrast, for highly educated workers, the raw gender pay gap increases across the earnings distribution, peaking at the median (20% at the 50th percentile) and declining slightly at the top (19% at the 75th percentile). Overall, among highly educated workers, the earnings gap is more pronounced at the middle (50th percentile) and top (90th percentile) of the distribution, while for low-educated workers, it is most significant at the bottom (10th percentile).

Table 3

Raw earnings difference by educational attainment

(log points)

Percentiles	Low-educated	Highly educated
Mean	0.3538	0.1163
10^{th} percentile	0.5108	0.1542
25^{th} percentile	0.2231	0.1542
50^{th} percentile	0.3365	0.1823
75^{th} percentile	0.4855	0.1744
90^{th} percentile	0.3668	0.1904

Source: author's calculations based on *KCHS (2021)* data.

4.3 Kernel density estimation of earnings

Figure A3 (see in Appendix) displays kernel density estimates of earnings distributions by gender and education level. The distance between the density curves for men and women reflects the magnitude of the raw gender pay gap. For both low-educated and highly educated groups, the earnings distribution is skewed in favor of men. However, this disparity is more pronounced among low-educated workers compared to their highly educated counterparts. The greater separation between the male and female earnings density curves in the low-education group is underscoring that the raw gender pay gap is larger for low-educated workers than for highly educated workers.

The kernel density plot in Appendix Figure A3a) clearly shows that highly educated workers earn more than low-educated ones, as their earnings distribution is skewed to the right, indicating higher income levels. In Appendix Figure A3b), the earnings distribution for highly educated workers shifts noticeably to the right compared to low-educated workers for both men and women. Additionally, earnings are more dispersed among highly educated workers, highlighting a more pronounced gender pay gap among low-educated workers. Among low-educated[11] men and women, the density of women's earnings is higher in the lower region of the distribution, indicating that a larger proportion of low-educated women are low-wage earners compared to men. The earnings gap persists through the median quartile but narrows significantly in the upper tail of the distribution. Notably, even in the lower quantiles of the earnings distribution, women earn less than men, and

[11] Low education implies basic education which encompasses primary, post primary, and secondary.

this disparity persists in the upper end of the lower earnings spectrum, where men still earn more than women. This suggests that even in low-paying jobs, men tend to earn higher wages than women. Overall, low-educated men are considerably more likely than women to have log earnings of around 8.5 log points or higher. Generally, the unadjusted gender pay gap is more prominent among low-educated men and women across the earnings distribution, although it diminishes significantly in the upper tail of the distribution.

Similarly, when examining highly educated men and women (in Appendix Figure A3b), we observe comparable patterns. First, results confirm that the raw earnings disparity between highly educated men and women is slightly narrower compared to low-educated individuals. Second, in the lower and middle ranges of the distribution highly educated men earn more than women, and this gap persists across the entire earnings spectrum, though it narrows significantly in the upper tail. These findings highlight that the Kenyan labor market likely exhibits a „sticky floor" effect, where women face greater challenges in advancing their earnings compared to men, particularly among low-educated workers. This suggests that structural barriers disproportionately affect women's ability to progress in the labor market, especially at lower education levels.

4.4 Mean characteristics by gender

Table 4 provides summary statistics of the covariates used to model earnings distributions, computed on the sample of employed workers, and disaggregated by gender and educational attainment. The covariates include variables commonly used in the Mincer model, capturing differences in human capital (e.g., age and job tenure), local labor market conditions (e.g., geographical area of residence), job tasks (e.g., occupation and type of employment contract), firm characteristics (e.g., firm size and sector of employment), and individual demographic factors (e.g., age and marital status). Variables controlling for job characteristics, such as occupation, are potentially endogenous; these are included in the model to help approximate the distribution of unobserved characteristics. As a result, the estimated coefficients for these variables are not intended to have a structural interpretation but rather to provide insights into their association with earnings outcomes.

Table 4

Summary statistics of the covariates of workers by gender and education

Denomination	Low-educated				Highly educated			
	men		women		men		women	
	mean	standard devia-tion	mean	standard devia-tion	mean	standard devia-tion	mean	standard devia-tion
Gross monthly earnings	8.566	1.394	8.213	1.385	10.145	1.267	10.029	1.096
Age (years)	35.757	11.428	34.767	10.733	36.954	9.971	35.924	10.090
Potential experience	14.009	11.074	13.025	10.373	14.966	9.951	13.942	10.062
Married	0.651	0.476	0.513	0.499	0.785	0.410	0.651	0.476
Household size	4.276	2.529	4.561	2.400	3.891	2.305	3.983	2.108
Tenure (in years)	6.871	7.506	6.432	7.362	8.757	8.398	9.029	8.927
Hours of work (weekly)	51.319	18.441	43.595	17.748	47.636	13.720	43.945	11.048
Residence								
Rural	0.619	0.485	0.595	0.490	0.406	0.491	0.390	0.488
Urban	0.380	0.485	0.404	0.490	0.593	0.491	0.609	0.488
Occupation								
Administrators, and managers	0.013	0.112	0.010	0.099	0.051	0.220	0.0404	0.197
Professionals	0.032	0.176	0.045	0.207	0.439	0.496	0.603	0.489
Technicians and associate professionals	0.027	0.161	0.013	0.112	0.111	0.314	0.057	0.232
Secretarial and clerical services	0.005	0.070	0.012	0.107	0.013	0.112	0.059	0.234
Service workers and market sales workers	0.141	0.349	0.190	0.392	0.155	0.362	0.151	0.357
Agriculture, forestry, and fishery workers	0.246	0.431	0.377	0.484	0.042	0.201	0.029	0.168
Craft and trade related workers	0.238	0.426	0.046	0.209	0.092	0.289	0.017	0.128
Plant and machine operators and assemblers	0.144	0.351	0.019	0.136	0.070	0.255	0.010	0.098
Elementary occupations	0.151	0.358	0.288	0.453	0.026	0.157	0.033	0.179
Firm size (number of employees)								
10–49	0.158	0.364	0.133	0.340	0.439	0.496	0.517	0.500
50–99	0.020	0.141	0.018	0.132	0.040	0.195	0.060	0.237
100 and above	0.070	0.255	0.060	0.238	0.157	0.364	0.125	0.331
Employment sector								
Public sector	0.074	0.261	0.066	0.248	0.527	0.499	0.624	0.484
Private formal	0.083	0.276	0.074	0.261	0.219	0.414	0.225	0.418
Private informal	0.842	0.364	0.860	0.346	0.252	0.434	0.149	0.356
Religion								
Christianity	0.844	0.362	0.943	0.230	0.908	0.289	0.933	0.250
Labor Union	0.037	0.189	0.024	0.152	0.243	0.429	0.277	0.448
N	3,427		1,726		783		717	

Source: author's calculations based on *KCHS (2021)* data.

Highly educated men earn significantly more on average, with gross monthly earnings of 10.145 log points, compared to highly educated women (10.0289 log points) and low-educated workers, particularly low-educated women, who have the lowest gross monthly earnings at 8.213 log points. On average, highly educated individuals are older than low-educated individuals with highly educated men being 37 years old and both highly educated and low-educated women averaging 36 years. Highly educated men also have more potential experience, averaging 15 years–one year more than highly educated women and two years more than low-educated women. Marriage rates are higher among men than women for both low-educated (65.1% of men vs. 51.3% of women) and highly educated (78.5% of men vs. 65.1% of women) workers. To account for the potential impact of job tenure on earnings, we include a continuous variable, measuring years in the current occupation. Highly educated women have a slightly longer average job tenure of 9 years compared to their male counterparts and low-educated workers.

Low-educated men work longer hours in their primary jobs compared to low-educated women and highly educated workers of both genders. Highly educated workers are predominantly concentrated in urban areas, likely due to better access to skilled and earnings-based employment, while low-educated workers are more common in rural regions. Additionally, highly educated workers tend to have smaller households than their low-educated counterparts. This trend reflects the preference among highly educated women for fewer children, prioritizing quality – such as better education and health outcomes – over quantity. Notably, household size is used as an exclusion restriction in the selection equation but does not factor into the wage distribution analysis.

Highly educated workers are more likely to hold public sector jobs, with 52.7% of highly educated men and 62.4% of highly educated women employed in such roles. In contrast, low-educated workers are predominantly concentrated in the private informal sector, with 84.2% of men and 86% of women in these positions. In earnings modeling, occupation type is captured using dummy indicators expected to be significant. Previous studies (e.g., *Bayard et al., 2003; Addabbo–Favaro, 2011; Orraca et al., 2016; Ismail et al., 2017*) suggest that occupational segregation, particularly for women, explains a substantial portion of the gender pay gap. In the sample, low-educated workers are primarily employed in blue-collar, craft, and elementary occupations, while highly educated women are more likely than highly educated men to work as professionals (60.3% of women vs. 43.9% of men). Furthermore, firm size is categorized into four indicators; among low-educated workers, 15.8% of men and 13.3% of women work in small firms, 2% of both genders in medium size firms, and 7% of men and 6% of women in large firms. For highly educated workers, more women (52%) than men (44%) are employed in small firms, while slightly more men than women work in large firms. Additionally, highly educated workers are more likely to belong to labor unions

(27.7% of women and 24.3% of men) compared to low-educated workers (3.7% of men and 2.4% of women). This suggests that low-educated workers are often in more vulnerable and less protected jobs.

5. Estimation results and discussions

5.1 Probability of participation in employment

Table 5 presents the estimated parameters of the probit model for the employment selection equation, disaggregated by gender and educational attainment. The coefficients reveal the direction of each covariate's impact on the probability of employment participation. A positive coefficient suggests that an increase in the corresponding variable raises the likelihood of an individual being employed.

For both highly educated and low-educated workers, the likelihood of public sector employment rises with age, whereas private sector employment declines with age, except for low-educated women, where the effect is insignificant. Residing in urban areas, compared to rural areas (the base group), reduces the probability of employment in either public or private sector for both highly educated and low-educated men and women. The estimated parameters for family-related factors indicate that Kenya follows a male/female breadwinner model, with married women more likely than men to work in the public sector, particularly among highly educated married women. Both highly educated and low-educated men and women are more likely to engage in employment as household size increases. This may reflect the need to support larger families, as more children often correlate with greater labor supply, either through longer work hours or increased labor market participation, to meet family needs.

Among highly educated individuals, women with diplomas and bachelor's degrees are more likely to be employed, while the opposite is true for men with diploma-level education. This gender disparity may stem from educational segregation, as women in Kenya often pursue less „prestigious" and more stereotypical fields of study, which typically offer fewer opportunities for advanced education and lower wages compared to men with equivalent qualifications *(KNBS, 2023)*. Additionally, if jobs requiring post-secondary education demand greater work commitment, women may face challenges balancing career and family care responsibilities, making them more likely to withdraw from such opportunities. Finally, the log-likelihood ratio (LR) test for non-random selection into employment, reported at the bottom of Table 5, rejects the null hypothesis of no sample selection for both men and women, as well as for highly educated and low-educated individuals.

Table 5

Estimation results for multinomial probit selection equation into employment by gender and education

Denomination	Female		Male	
	public sector	private sector	public sector	private sector
Highly educated				
Age	0.0580***	–0.0129	0.0564***	–0.0145
	(0.00912)	(0.0115)	(0.00909)	(0.0104)
Married	0.847***	–0.0232	0.225	–0.590***
	(0.168)	(0.194)	(0.201)	(0.197)
Household size	0.0284	0.0631	–0.00706	0.0698*
	(0.0398)	(0.0437)	(0.0367)	(0.0392)
Urban	–0.827***	–0.528**	–0.813***	–0.295
	(0.176)	(0.206)	(0.167)	(0.183)
Primary	–	–		–
Secondary	–	–		–
Diploma	0.00382	1.126	–0.104	1.423**
	(0.398)	(0.700)	(0.341)	(0.588)
Bachelors	0.533	0.406	0.524	0.947
	(0.420)	(0.733)	(0.349)	(0.600)
Constant	–1.429**	–0.733	–1.153**	–0.324
	(0.580)	(0.845)	(0.532)	(0.739)
Observations	717		783	
LR sample selection test	χ^2 (12) = 172.23; p–value=0.000		χ^2 (12) = 198.45; p–value=0.000	
Low-educated				
Age	0.0319***	–0.00879*	0.0385***	0.00232
	(0.00559)	(0.00451)	(0.00816)	(0.00662)
Married	0.140	–0.512***	0.342*	–0.302**
	(0.155)	(0.111)	(0.175)	(0.134)
Household size	0.0803***	0.0640***	0.0292	0.0184
	(0.0252)	(0.0204)	(0.0377)	(0.0295)
Urban	–0.410***	–0.700***	–0.142	–0.634***
	(0.120)	(0.0943)	(0.177)	(0.138)
Primary	–0.778**	0.193	0.0254	1.678***
	(0.357)	(0.312)	(0.476)	(0.382)
Secondary	–0.392	–0.540*	0.438	0.792**
	(0.353)	(0.310)	(0.467)	(0.379)
Diploma	–	–	–	–
Bachelors	–	–	–	–
Constant	–1.024**	2.755***	–1.977***	1.028**
	(0.421)	(0.353)	(0.569)	(0.451)
Observations	3,427		1,726	
LR sample selection test	χ^2 (12) = 373.68; p–value=0.000		χ^2 (12) = 182.50; p–value=0.000	

Note: standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Source: author's calculations based on *KCHS (2021)* data.

5.2 The impact of covariates on Mincer earnings function

In this section, the key findings from the decomposition analysis are presented, which estimate the returns to characteristics and predict monthly earnings for men and women at specific percentiles using quantile regressions. As outlined in the descriptive statistics section, the covariates' impact on the earnings density functions is modeled flexibly, allowing for varying effects across different quantiles of the earnings distribution. Tables 6 and 7 present the selectivity-corrected[12] estimation results, accounting for potential non-random selection into employment, and show the effects of covariates at selected quantiles for men and women by educational attainment.

In a Mincer-type earnings equation, a significant portion of earnings is explained by human capital factors, particularly education and experience. As previously highlighted, the subsamples of low-educated and highly educated workers are heterogeneous. Beyond formal education, the dataset enables the construction of a variable for potential labor market experience. This is calculated by subtracting 6 years of pre-schooling and the years spent in formal education from an individual's actual age, yielding the total number of years they have theoretically been in the workforce since their first job. This variable is treated as continuous and, following standard practice, is included in the earnings equation in a quadratic form to reflect its positive but diminishing marginal effect on earnings.

However, caution is warranted when using this "theoretical" measure of experience, as it may not accurately capture actual years in the labor market. This proxy does not account for periods of absence due to unemployment, inactivity, or other reasons such as illness or parenthood. As a result, theoretical experience may overestimate true working years. This measurement issue affects both men and women, though empirical evidence suggests it is more pronounced for women due to interruptions such as maternity leave *(Addabbo–Favaro, 2011)*. In order to address these limitations, the model includes additional regressors such as variables related to productive sectors, firm size, tenure and occupational characteristics. Furthermore, the specification incorporates a dummy variable for labor union membership, reflecting bargaining characteristics, as well as demographic dummies for marital status and residence.

The estimated parameters shed light on how various covariates influence the Mincer earnings function. Characteristics with a positive effect are associated with an earnings premium, meaning that individuals possessing these attributes are likely to earn higher wages compared to the reference group. Potential experience

[12] Coefficient estimates without sample selection are not reported in the paper but available upon request.

exhibits a quadratic relationship with earnings, positively and significantly impacting earnings for both highly educated and low-educated workers, with a stronger effect observed at the lower end of the earnings distribution *(Padayachie, 2015; Kabubo-Mariara, 2003; Omanyo, 2021; Agessa et al., 2013)*. The positive coefficient suggests that older workers earn higher earnings due to their greater experience. However, the non-linear relationship indicates that earnings growth slows with age, particularly as highly educated workers approach retirement, confirming an inverted U-shaped pattern.

Table 6

Coefficient estimates for the covariates corrected for sample selection at selected quantiles of the earnings distribution by education – Male model

Denomination	25th	50th	75th
Highly educated			
Potential experience	0.0859**	0.0627***	0.0600***
	(0.0398)	(0.0219)	(0.0142)
Square of experience	–0.00135*	–0.000975**	–0.000906***
	(0.000690)	(0.000414)	(0.000335)
Married	0.235	0.163	0.176
	(0.178)	(0.145)	(0.111)
Hours of work	–0.00133	0.000676	–0.00411**
	(0.00314)	(0.00229)	(0.00168)
Tenure	0.0324***	0.0210***	0.0153**
	(0.00911)	(0.00426)	(0.00668)
Education			
Primary	–	–	–
Secondary	–	–	–
Diploma	–0.828***	–0.726***	–0.795***
	(0.140)	(0.105)	(0.254)
Bachelors	–0.0857	–0.267**	–0.365
	(0.175)	(0.118)	(0.264)
Public sector	0.104	0.156	0.0506
	(0.136)	(0.0997)	(0.100)
Private informal	–0.598***	–0.454***	–0.414***
	(0.154)	(0.142)	(0.119)
Occupations			
Administrators, and managers	0.471	0.552**	0.854***
	(0.309)	(0.237)	(0.308)
Professionals	0.181	0.451**	0.701**
	(0.337)	(0.221)	(0.274)

(Table continues on the next page.)

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Denomination	25th	50th	75th
Highly educated			
Technicians and associate professionals	0.275	0.572***	1.007***
	(0.355)	(0.208)	(0.232)
Secretarial and clerical services	–0.0328	0.353*	0.634
	(0.406)	(0.207)	(0.410)
Service workers and market sales workers	0.288	0.320	0.611**
	(0.312)	(0.221)	(0.255)
Agriculture, forestry, and fishery workers	–0.794	0.0847	0.505*
	(0.648)	(0.391)	(0.270)
Craft and trade related workers	0.185	0.291	0.612**
	(0.375)	(0.253)	(0.243)
Plant and machine operators and assemblers	0.531	0.559**	0.793***
	(0.339)	(0.223)	(0.254)
Urban	–0.0845	0.0815	0.106
	(0.184)	(0.129)	(0.107)
Firm size			
10–49 employees	0.131	–0.0444	–0.0563
	(0.129)	(0.0957)	(0.0998)
50–99 employees	0.472	0.235	0.272
	(0.323)	(0.205)	(0.225)
100 and above	0.277	0.203**	0.223*
	(0.196)	(0.0908)	(0.131)
Labor union	0.235	0.220**	0.185**
	(0.162)	(0.0865)	(0.0885)
Mills ratio	1.196*	0.519	0.406
	(0.681)	(0.466)	(0.402)
Constant	8.262***	9.093***	9.675***
	(0.693)	(0.488)	(0.546)
Observations		783	
Pseudo R^2	0.333	0.3170.372	
Low educated			
Potential experience	0.0842***	0.0345***	0.0346***
	(0.0175)	(0.00757)	(0.00718)
Square of experience	–0.00125***	–0.000425***	–0.000552***
	(0.000391)	(0.000151)	(0.000133)
Married	0.214	0.221***	0.259***
	(0.167)	(0.0452)	(0.0563)
Hours of work	0.0140***	0.00875***	0.00526***
	(0.00260)	(0.000872)	(0.00114)
Tenure	–0.00645	0.00468*	0.00816***
	(0.00618)	(0.00245)	(0.00259)

(Table continues on the next page.)

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Denomination	25th	50th	75th
	Low educated		
Education			
Primary	–1.051**	–0.573***	–0.495***
	(0.458)	(0.107)	(0.159)
Secondary	–0.262	–0.180**	–0.135
	(0.369)	(0.0901)	(0.126)
Diploma	–	–	–
Bachelors	–	–	–
Public sector	0.118	0.236**	0.374***
	(0.159)	(0.116)	(0.0915)
Private informal	–0.443***	–0.268***	–0.294***
	(0.134)	(0.0600)	(0.0663)
Occupations			
Administrators, and managers	0.806***	0.781***	0.495***
	(0.174)	(0.124)	(0.129)
Professionals	0.0904	0.267***	0.337***
	(0.143)	(0.0726)	(0.118)
Technicians and associate professionals	0.215	0.447***	0.536***
	(0.182)	(0.0727)	(0.131)
Secretarial and clerical services	0.559*	0.579***	0.528***
	(0.326)	(0.120)	(0.188)
Service workers and market sales workers	–0.0816	0.173***	0.227***
	(0.125)	(0.0482)	(0.0523)
Agriculture, forestry, and fishery workers	–0.516***	0.0273	0.0239
	(0.177)	(0.0351)	(0.0406)
Craft and trade related workers	–0.0953	0.330***	0.478***
	(0.147)	(0.0538)	(0.0558)
Plant and machine operators and assemblers	–0.202	0.409***	0.528***
	(0.272)	(0.0617)	(0.0701)
Urban	–0.255	–0.0980	–0.0430
	(0.188)	(0.0703)	(0.0896)
Firm size			
10–49 employees	0.320***	0.244***	0.165***
	(0.0881)	(0.0532)	(0.0479)
50–99 employees	0.378**	0.252*	0.102
	(0.180)	(0.141)	(0.0658)
100 and above	0.587***	0.493***	0.408***
	(0.104)	(0.0525)	(0.0645)
Labor union	0.102	0.218***	0.0784*
	(0.206)	(0.0660)	(0.0459)
Mills ratio	1.324***	0.689***	0.499***
	(0.448)	(0.148)	(0.188)
Constant	6.377***	7.589***	8.323***
	(0.516)	(0.206)	(0.185)
Observations		3,427	
Pseudo R^2	0.108	0.127	0.160

Note: bootstrap standard errors with 20 replications in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: author's calculations based on *KCHS (2021)* data.

Marital status significantly influences the earnings distribution for low-educated men and highly educated women. Married low-educated men earn notably higher earnings at the median and upper percentiles of the earnings distribution, while highly educated women earn significantly higher wages at the lower and median percentiles compared to their unmarried (base-group) counterparts. Marriage is often perceived by employers as a marker of stability and discipline, potentially leading to higher earnings due to the view that married individuals are more dependable and committed. In contrast, low-educated women face an earnings penalty at the median percentiles, though the effect is statistically insignificant. This may reflect the disproportionate burden of the „second shift" that women often bear, causing them to prioritize household responsibilities over market labor. Additionally, Kenya's relatively high fertility rate may lead employers to associate marriage with potential career interruptions, possibly resulting in discrimination against married women.

Weekly hours worked in an individual's primary occupation have a positive and significant impact on earnings for both low-educated men and women across the earnings distribution. Tenure, measured as the number of years in the current occupation, significantly boosts earnings for highly educated men across all wage levels, while for low-educated men, the effect is significant only at the median and upper quantiles. For women, tenure significantly affects earnings only for low-educated women at the upper end of the distribution. The impact of covariates on earnings varies by sector, gender, and educational attainment. Both men and women earn higher wages in the public sector compared to the private formal sector (the reference category), while employment in the private informal sector is associated with lower earnings. Additionally, residential location influences earnings, with urban areas showing significant pay disadvantages. These disadvantages are particularly pronounced for low-educated men across the entire wage distribution and for low-educated women at the lower end of the distribution. This geographical heterogeneity is a structural characteristic of the Kenyan labor market, extending beyond earnings to include disparities in unemployment and employment rates across regions *(KNBS, 2023)*.

Table 7

Coefficient estimates for the covariates corrected for sample selection at selected quantiles of the earnings distribution by education – Female model

Denomination	25th	50th	75th
Highly educated			
Potential experience	0.103***	0.0892***	0.0296
	(0.0254)	(0.0175)	(0.0196)
Square of experience	–0.00157***	–0.00156***	–0.000247
	(0.000556)	(0.000286)	(0.000540)
Married	0.352***	0.326**	0.0903
	(0.136)	(0.129)	(0.144)
Hours of work	0.00503	0.00643*	–1.16e–05
	(0.00312)	(0.00358)	(0.00326)
Tenure	0.0112	0.00935	0.00545
	(0.00681)	(0.00896)	(0.00571)
Education			
Primary	–	–	–
Secondary	–	–	–
Diploma	–0.990**	–0.815***	–1.418***
	(0.398)	(0.170)	(0.377)
Bachelors	–0.205	–0.180	–0.854**
	(0.397)	(0.159)	(0.351)
Public sector	0.205**	0.118*	0.0539
	(0.0918)	(0.0713)	(0.120)
Private informal	–0.775***	–0.704***	–0.627***
	(0.160)	(0.149)	(0.183)
Occupations			
Administrators, and managers	0.620**	0.475**	0.433**
	(0.298)	(0.205)	(0.188)
Professionals	–0.0258	–0.00844	0.238
	(0.260)	(0.222)	(0.174)
Technicians and associate professionals	0.485	0.391	0.408*
	(0.346)	(0.240)	(0.231)
Secretarial and clerical services	0.0395	0.0145	0.377
	(0.278)	(0.246)	(0.250)
Service workers and market sales workers	0.287	0.250	0.480**
	(0.276)	(0.213)	(0.213)
Agriculture, forestry, and fishery workers	–0.265	–0.412	0.115
	(0.411)	(0.298)	(0.358)
Craft and trade related workers	0.205	–0.0451	–0.147
	(0.286)	(0.312)	(0.387)
Plant and machine operators and assemblers	0.326	0.304	0.226
	(0.348)	(0.314)	(0.301)
Urban	0.0344	0.0656	0.105
	(0.122)	(0.112)	(0.0910)

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(Continued.)

Denomination	25th	50th	75th
Highly educated			
Firm size			
10–49 employees	0.0663	0.0769	0.0617
	(0.108)	(0.0922)	(0.0891)
50–99 employees	0.0634	0.190	0.349**
	(0.213)	(0.158)	(0.137)
100 and above	0.161	0.228*	0.0941
	(0.137)	(0.136)	(0.191)
Labor union	0.519***	0.499***	0.240**
	(0.0916)	(0.0708)	(0.0985)
Mills ratio	1.440***	0.981**	0.0471
	(0.540)	(0.449)	(0.361)
Constant	7.955***	8.618***	10.87***
	(0.681)	(0.431)	(0.536)
Observations		717	
Pseudo R^2	0.337	0.320	0.272
Low educated			
Potential experience	0.0956***	0.0354**	0.0415**
	(0.0244)	(0.0144)	(0.0174)
Square of experience	–0.00158***	–0.000597**	–0.00705***
	(0.000451)	(0.000247)	(0.000217)
Married	0.0523	–0.0266	0.0847
	(0.222)	(0.127)	(0.129)
Hours of work	0.0169***	0.00909***	0.00517***
	(0.00253)	(0.00136)	(0.00169)
Tenure	–0.00458	0.00408	0.00973***
	(0.00766)	(0.00392)	(0.00315)
Education			
Primary	–0.433**	–0.115	–0.146
	(0.169)	(0.182)	(0.133)
Secondary	0.397*	0.200	0.243
	(0.224)	(0.204)	(0.211)
Diploma	–	–	–
Bachelors	–	–	–
Public sector	0.379*	0.193*	0.230
	(0.201)	(0.102)	(0.144)
Private informal	–0.375**	–0.370***	–0.252***
	(0.148)	(0.105)	(0.0876)
Occupations			
Administrators, and managers	–0.0155	0.465	0.950**
	(0.299)	(0.392)	(0.391)
Professionals	–0.299	–0.0678	0.220
	(0.225)	(0.163)	(0.157)

(Table continues on the next page.)

(Continued.)

Denomination	25th	50th	75th
Low educated			
Technicians and associate professionals	0.279	0.531***	0.352**
	(0.375)	(0.169)	(0.175)
Secretarial and clerical services	0.465*	0.622**	0.621***
	(0.260)	(0.298)	(0.180)
Service workers and market sales workers	–0.295***	0.000971	0.120*
	(0.113)	(0.0547)	(0.0617)
Agriculture, forestry, and fishery workers	–0.898***	–0.310***	–0.181***
	(0.141)	(0.0649)	(0.0547)
Craft and trade related workers	0.104	0.215***	0.225**
	(0.165)	(0.0829)	(0.102)
Plant and machine operators and assemblers	0.110	0.276**	0.160
	(0.252)	(0.118)	(0.134)
Urban	–0.0579	0.174	0.0604
	(0.153)	(0.112)	(0.113)
Firm size			
10–49 employees	0.376***	0.243**	0.329***
	(0.133)	(0.101)	(0.0759)
50–99 employees	0.600**	0.595***	0.622***
	(0.250)	(0.211)	(0.120)
100 and above	0.666***	0.489***	0.402***
	(0.149)	(0.104)	(0.0761)
Labor union	0.244	0.259	0.377*
	(0.563)	(0.160)	(0.196)
Mills ratio	0.783*	0.182	0.332
	(0.436)	(0.253)	(0.331)
Constant	6.061***	7.845***	8.002***
	(0.875)	(0.487)	(0.608)
Observations		1,726	
Pseudo R^2	0.169	0.141	0.188

Note: Bootstrap standard errors with 20 replications in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: author's calculations based on *KCHS (2021)* data.

The impact of occupational categories on earnings also varies significantly by gender and educational attainment. For example, the occupational group "legislators, administrators, and managers" is linked to higher earnings for both highly and low-educated men and women compared to those in elementary occupations (the reference group). Similarly, working as a "professional, technician, and associate professional" boosts earnings for men and women at the median and upper levels of the earnings distribution. Additionally, „clerical jobs" are associated with higher earnings for low-educated men and women, with the effect being significant across the entire earnings distribution. In the „agriculture, forestry, and fishery" sector, earnings increase for highly educated men at the 75th percentile and for low-educated men at the 25th percentile, while low-educated women in this sector experience earnings penalties across all earnings levels. Furthermore, male-dominated occupations such as „craft and trade-related work" and „plant and machine operators and assemblers" are associated with higher earnings for low-educated men and women at the median and upper quartiles of the wage distribution. These findings highlight the nuanced and varied effects of occupational categories on earnings across different segments of the labor market.

Employment in small to large firms (with 10 or more employees) is associated with higher earnings, particularly for low-educated men and women. Labor union membership also correlates with higher earnings for both genders, with the effect being most pronounced among highly educated women across the entire earnings distribution, low-educated women at the 75th percentile, and highly and low-educated men at the median and upper quantiles. This underscores the strong bargaining power of Kenyan labor unions, consistent with findings from *Butcher and Rouse (2001)* and *Ntuli (2007)*. Lastly, the selectivity-correction term (the inverse of Mill's ratio), which accounts for selectivity bias using household size as an exclusion restriction, is positive and significant for low-educated men across the entire earnings distribution, as well as for highly educated women at the lower and median percentiles and low-educated women at the bottom of the distribution. This indicates the presence of selectivity bias in the model, reflecting the dual burden faced by women with large families due to the „second shift" and the pressure on men to provide for their households.

5.3 Decomposition of the gender pay gaps by education across the earnings distribution

Present study employs the simulation algorithm developed by *Machado and Mata (2005)* to decompose the gender pay gap, corrected for sample selection, into two components for both low and highly educated individuals: one attributable to gender differences in the distribution of individual characteristics and the other to gender differences in the returns to those characteristics, often referred to as the unexplained portion of the pay gap. This approach aligns with the spirit of *Oaxaca (1973)* and *Blinder's (1973*) decomposition of mean wage effects but extends the analysis across the entire earnings distribution. The decomposition relies on constructing counterfactual distributions that estimate what the earnings distribution would look like if men had the same characteristics as women. Specifically, two counterfactual densities are generated: the first represents the log earnings distribution for women if they possessed the same labor market characteristics as men but were still paid according to the female earnings structure. The second density represents the hypothetical distribution if women retained their own labor market characteristics but were compensated according to the male earnings structure *(Albrecht et al., 2003; Machado–Mata, 2005; Arulampalam et al., 2007; de la Rica et al., 2008)*. In essence, this method allows to analyze earnings disparities between men and women across different education levels by exploring counterfactual scenarios – either adopting men's labor market characteristics while maintaining women's earnings structure or retaining women's characteristics while applying the male wage structure.

In addition to presenting results separately for highly and low-educated workers, in line with the article's focus, the author first presents findings for the entire sample of workers – the pooled model – where both groups are treated indistinctly. This approach demonstrates how the results might differ if the analysis was conducted without distinguishing between educational levels, as is common in much of the literature on gender pay gap decomposition.[13] Combining the two groups could lead to significant errors in evaluating earnings differentials; however, separating them reveals clear distinctions between the two. For the entire sample, the observed gender pay gap exhibits a decreasing trend, particularly at the upper quantiles of the earnings distribution (in Appendix Figure A4a). This indicates that women face a larger earnings penalty at the lower end of the distribution, but the gap narrows as earnings increase, especially in the top decile. The decomposition further reveals that women possess significantly better productive characteristics than men (in Appendix Figure A4b), and the portion of the gap explained by these differences favors women. As earnings rise, the improvement in female characteristics outpaces that of male characteristics, causing the explained component of the gap to increasingly favor women, reaching 0.332 log points (reduces by 39.4%) at the highest wage levels.

Conversely, at the same earnings deciles, the unexplained portion of the pay gap (in Appendix Figure A4c) amounts to 0.406 log points (50.1%) in favor of male workers, with the largest differences in rewards occurring at the lower end of the earnings distribution. To sum up, a pooled analysis suggests that the gender pay gap narrows as women reach higher earnings levels. Additionally, women's superior productive characteristics increasingly offset differences in rewards across the earnings distribution, allowing them to reverse the observed gender pay gap in their favor at the highest percentiles. These findings align with those of *Arulampalam et al. (2007)* and *Addabbo and Favaro (2011).*

Table 8 presents the quantile decomposition results with selection correction for low-educated workers. The first column shows the observed raw pay gap, defined as the difference between male and female unconditional log earnings at

[13] The decomposition, in this case, is carried out on quantile estimates performed on the whole sample of workers, including both highly- and low-educated. I would be glad to provide quantile estimate results upon request.

various quantiles of the earnings distribution *(Albrecht et al., 2003; Machado–Mata, 2005)*. The second column displays the gender pay gap that would exist if women had the same characteristics as men, representing the portion of the gap explained by differences in observable productivity-related characteristics between genders. The third column presents the unexplained component of the gender pay gap, arising from differences in the remuneration of the same characteristics after correcting for sample selection. The counterfactual gap illustrates the disparities between the quantiles of women's log earnings distribution and the corresponding quantiles of a counterfactual distribution. This counterfactual distribution is constructed by applying the male earnings structure to women's characteristics, effectively capturing the differences in returns between men and women when women retain their own characteristics but are compensated according to male wage rates.

Table 8

Gender pay gap (in log points) for low educated workers

Quantile	Observed wage gap	Characteristics	Coefficients	Counterfactual
0.10	0.288*	–0.223**	0.511***	0
	(0.156)	(0.103)	(0.171)	(0.115)
0.20	0.223**	–0.0645	0.288***	0.223**
	(0.0892)	(0.0463)	(0.0777)	(0.102)
0.30	0.329***	0	0.329***	0
	(0.0712)	(0.0226)	(0.0730)	(0.0374)
0.40	0.405***	0.0870	0.318***	–0.182***
	(0.0476)	(0.0727)	(0.0867)	(0.0601)
0.50	0.336***	0.154***	0.182***	–0.154***
	(0.0216)	(0.0336)	(0.0401)	(0.0458)
0.60	0.375***	0.134***	0.241***	–0.182***
	(0.0621)	(0.0209)	(0.0615)	(0.0351)
0.70	0.511***	0.223***	0.288***	–0.203***
	(0.0179)	(0.0296)	(0.0344)	(0.0436)
0.80	0.470***	0.182***	0.288***	–0.223***
	(0.0462)	(0.0270)	(0.0388)	(0.0347)
0.90	0.288***	0.134*	0.154**	–0.182***
	(0.0596)	(0.0686)	(0.0459)	(0.0368)

Note: standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Standard errors produced through bootstrapping using 100 replications.
Source: author's calculations based on *KCHS (2021)* data.

Table 8 and Figure A5b) (see in Appendix) show an inconsistent pattern in the observed gender pay gap across the earnings distribution. The gap peaks at the 70th percentile with 0.511 log points (66.7%) and is lowest at the 20th percentile with 0.223 log points (24.5%). Specifically, the gap rises steadily from the 2nd decile (24.5%) to the 4th decile (49.9%), dips slightly at the median (39.9%), then climbs to its highest point at the 70th percentile (approximately 67%), before dropping sharply to 33.4% at the 90th percentile. Notably, women earning above the 20th percentile emerge as the most disadvantaged group. These findings indicate the gender pay gap tends to widen in the upper tiers of the earnings distribution. While no consistent pattern emerges across the distribution, the larger pay gap in the higher quantiles suggests the presence of a „glass ceiling" among low-educated workers. This implies that high-wage earners within this group, particularly women, face earnings discrimination and barriers in advancing into higher-paying positions. The results partially align with *Padayachie (2015),* who found the largest gender wage gap for low-educated individuals at the top two quantiles. However, they contrast with *Ntuli (2007)* and *Mussida and Picchio (2014),* who identified a „sticky floor" effect.

If men and women had the same characteristics (Table 8, second column, and Figure A5c in Appendix), women would still face significant earnings penalties, except at the lower end of the earnings distribution, where the gender pay gap would decrease by 6.7 to 24.9% based on observed characteristics. This suggests that women at the bottom of the earnings distribution possess somewhat better productivity-related endowments or observable traits. However, across the broader earnings distribution, low-educated women experience a larger earnings penalty, ranging from 14.3 to 24.9%, with the most pronounced effect at the 70th percentile. These findings align with those of *Mussida and Picchio (2014).*

The gender pay gap, due to differences in the remuneration of the same characteristics (column 3 and Figure A5d in Appendix), shows that all estimates are positive and significant across the entire distribution. This indicates that men's productivity-related characteristics are rewarded more highly, while women's productivity endowments are undervalued. Based on differences in returns to productivity-related traits, the gender pay gap favors men and is most pronounced at the lower end of the earnings distribution. After accounting for selectivity bias and unobserved heterogeneity, women at the bottom of the distribution (low-wage earners) face greater pay discrimination (66.7%) compared to those at the top (16.6%). The pay gap narrows significantly at the upper end of the distribution, potentially due to the strengthening of minimum wage policies in Kenya, which advocate for pay increases for unionized workers. These findings align with *Padayachie (2015),* which highlighted wage discrimination against low-educated women in South Africa.

The empirical findings highlight two key insights. First, the earnings penalty for low-educated women significantly increases when correcting for nonrandom selection into employment, particularly in the upper-lower quartiles, median, and upper quartiles of the earnings distribution. This suggests that low-educated women in these segments are more positively selected into employment than comparable men, meaning those who would receive the lowest returns from working are less likely to be employed than their male counterparts. Therefore, accounting for sample selection bias is crucial in order to avoid underestimating the role of education in shaping labor market inequalities. Second, for low-educated women, there is no clear evidence of a tougher „glass ceiling" or „sticky floor" after controlling for sample selection bias, despite a larger gender pay gap at the median and upper quartiles. Even when women share the same characteristics as men, they face greater barriers to reaching higher-paying positions. Additionally, based on differences in returns to observable characteristics, women experience significant pay discrimination, particularly at the lower end of the earnings distribution.

The counterfactual earnings gap reveals that estimates are negative across the distribution, except at the 20th percentile. This indicates the undervaluation of women's average productivity-related characteristics presently in the labor market. The negative pay gap suggests that if low-educated women were compensated using the male earnings structure while retaining their own characteristics, the gender pay gap would favor women and decline significantly, ranging from 16.7 to 24.5%. In other words, if women maintained their current characteristics but were paid at the same rate as low-educated men, their wages would rise substantially, leading to a notable reduction in the wage gap across the earnings distribution.

The quantile decomposition results for highly educated workers (Table 9) show that the earnings gap widens as one moves up the earnings distribution, though the rate of change varies across quantiles. The findings (in Appendix Figure A6a) provide clear evidence of a „glass ceiling" for highly educated workers, indicating that highly educated women in high-wage positions face earnings disadvantages, likely due to vertical occupational segregation. The pay gap increases steadily along the distribution from the second quantile (8%) to the 4th decile (24.5%), dips slightly at the median (15.4%), and then peaks at the 70th percentile (28.9%). It declines marginally at the 80th percentile (20.8%) but rises again at the top of the distribution (26.9%). The wage gap is larger in the median and upper quantiles compared to the lower quantiles and remains statistically significant across the distribution, except in the two deciles at the bottom. This suggests that as women advance in the earnings distribution, they encounter greater barriers in achieving higher income and positions, reinforcing the presence of a „glass ceiling." These results align with *Padayachie (2015),* which found that among highly educated individuals, the wage gap is substantial and significant in the upper quantiles of the earnings distribution.

If highly educated men and women had the same characteristics (Table 9, second column, and Figure A6b in Appendix), women would still face earnings penalties ranging from 4.7 to 8.9%, although the effect is statistically insignificant across the earnings distribution. Additionally, the gender pay gap, due to differences in returns to the same characteristics (column 3 and Figure A6c in Appendix), shows that all estimates are positive and significant from the 4th decile upward. This indicates that men's productivity-related endowments are rewarded more highly, while women's endowments are undervalued. Based on differences in returns to these productivity-related traits, the pay gap favors men and is most pronounced at the top of the earnings distribution, reaching 26.9%. These results demonstrate that the primary driver of the gender pay gap among highly educated workers is the unexplained component – differences in returns to productivity-related characteristics – associated with discriminatory practices in the labor market, such as taste-based and statistical discrimination.

Table 9

Gender pay gap (in log points) for highly educated workers

Quantile	Observed pay gap	Characteristics	Coefficients	Counterfactual
0.10	0	0	0	0.0690
	(0.101)	(0)	(0.101)	(0.104)
0.20	0.0800	0.0800	0	0
	(0.125)	(0.104)	(0.112)	(0.0904)
0.30	0.182*	0	0.182	0
	(0.102)	(0.0976)	(0.115)	(0.0713)
0.40	0.223**	0.0408	0.182*	–0.0870
	(0.0999)	(0.0917)	(0.0941)	(0.102)
0.50	0.143*	0	0.143**	0
	(0.0849)	(0.0758)	(0.0669)	(0.0627)
0.60	0.223***	0.0460	0.177***	0
	(0.0679)	(0.0635)	(0.0639)	(0.0445)
0.70	0.254***	0.0852	0.169***	–0.0305
	(0.0640)	(0.0539)	(0.0544)	(0.0436)
0.80	0.189***	0.0506	0.139***	–0.0800
	(0.0481)	(0.0374)	(0.0418)	(0.0487)
0.90	0.238***	0	0.238***	–0.154***
	(0.0675)	(0.0131)	(0.0655)	(0.0510)

Note: standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Standard errors produced through bootstrapping using 100 replications.
Source: author's calculations based on *KCHS (2021)* data.

For highly educated workers, the counterfactual gender pay gap reveals that the estimates are negative in the upper quantiles of the earnings distribution. This negative gap indicates that if highly educated women were compensated using the male earnings structure, while retaining their average characteristics, the pay gap would favor women, with a significant effect among high-wage earners at the top of the distribution. In other words, for women in the upper tiers of the earnings distribution, maintaining their average characteristics but being paid at the same rate as highly educated men would lead to a substantial increase in their earnings, reducing the pay gap by 16.6%.

6. Discussion of the results

The findings from the decomposition analysis intersect critically with the structural and institutional dynamics in Kenya's labor market, especially in the context of education, vocational training, and labor market inequities. The results indicate that both low- and highly educated women face persistent earnings disparities, driven by the systemic undervaluation of their productivity characteristics and institutional barriers embedded in Kenya's labor market.

The results indicate that low-educated women across the earnings distribution are more positively selected into employment than comparable men, with the gender pay gap increasing as one moves up the distribution. However, the gap remains substantial at the lower quartiles, ranging from 33.3% at the 10th percentile to 49.9% at the 40th percentile. This pattern, particularly at the 40th percentile, may suggest the presence of a „sticky floor." One explanation for this phenomenon is a horizontal occupational segregation[14]. Women who might occupy lower-tier jobs suffer earnings penalty due to occupational segregation in such roles, or because of personal preferences, thereby self-selecting into occupations with flexibility. Low-educated women, in particular, are often segregated into occupations with limited responsibility and lower pay. This occupational segregation likely accounts for a significant portion of the gender pay gap *(Bayard et al., 2003; Addabbo–Favaro, 2011; Mussida–Picchio, 2014)*. Another explanation centers on gender differences in workforce attachment and the resulting propensity to participate in the labor market. Low-educated women who might occupy lower-tier jobs may demonstrate weaker workforce attachment compared to men with the same

[14] See *Blau and Khan (2006)* about the relevance of discrimination on the gender pay gap and *Brown et al. (1980)* on the role of occupational segregation in explaining the gender wage gap.

educational background. For example, these women might choose not to participate in the workforce due to preference-related reasons, such as valuing leisure over working time, or because they require greater flexibility to balance domestic responsibilities with market labor.

The gender pay gap for highly educated workers ranges from 8.3 to 28.9%. Highly educated women tend to narrow the gap at the lower end of the earnings distribution but lose this advantage as they progress to higher earnings levels. In contrast, the earnings differences between low-educated women and men are most pronounced in the median quantiles, particularly between the 4th and 8th deciles, before slightly decreasing as women approach the highest-paying positions. Notably, the gap at the top decile is similar to that at the bottom. All in all, the pay gap is more significant among low-educated workers compared to their highly educated counterparts, though highly educated women face a distinct „glass ceiling" effect.

The portion of the pay gap attributed to differences in the returns to characteristics is smaller for low-educated women, than the observed wage gap from the 4th decile to the top decile. This suggests that gender differences in returns do not fully explain the observed pay gap, indicating that part of the gap stems from productive characteristics that are more favorable for men. This is particularly evident at the lower end of the distribution, where low-educated women in the 1st and 2nd deciles can match male income profiles due to their superior productive characteristics. However, beyond the 3rd decile, men's better characteristics account for at most 24.9% of the gap. Across most of the distribution, the portion of the gap explained by differences in characteristics favors men from the 4th decile to the top decile. At the 3rd decile, women have productive characteristics similar to men, resulting in an observed gap that aligns with the gap due to differences in rewards. The estimated gap due to differences in rewards for characteristics is generally smaller for highly educated women than the observed wage gap, except at the 30th percentile, median, and 90th percentile. At all wage levels, differences in characteristics tend to favor men, and this disadvantage for women is further exacerbated by disparities in rewards. As a result, highly educated women face wage gaps at all earnings levels, driven by both differences in rewards and productive characteristics. Additionally, the gap in returns widens as wage rates increase, peaking at 26.9% at the top decile. Men's superior endowments offset any potential economic advantage from better characteristics, unlike the case for low-educated women.

The significant variation in the composition of the observed wage gap by education, coupled with the high incidence of characteristic differences among low-educated women, suggests that low-educated Kenyan women have achieved parity in primary and secondary education, while men tend to have more tertiary education. Despite this fact, low-educated women still face substantial pay penalties compared to highly educated women. These findings contrast with those of *McGuinness and Bennett (2007)* and *Addabbo and Favaro (2011),* who found that over-educated men earn 11% less than their well-matched counterparts, while over-educated women earn nearly 23% less than adequately matched women. Additionally, *Di Pietro and Urwin (2006)* observed that Italian graduates with education exceeding their job requirements earn lower wages than similarly educated peers in suitable positions, though the study did not analyze this phenomenon by gender.

Present study highlights that the pattern of earnings differentials between women and men varies significantly by education level in Kenya. A glass ceiling effect is evident only for highly educated women, whose pay gap increases steadily across the earnings distribution, particularly at the top decile. However, even at these higher earnings levels, the observed pay gap does not fully close due to the less favorable productive characteristics of highly educated women compared to their male counterparts. In contrast, low-educated women do not exhibit a clear glass ceiling or sticky floor effect; instead, their earnings gap tends to rise as they move from very low wage levels to the median quantiles. These findings align with those of *De la Rica et al. (2008)* and *Favaro and Magrini (2008),* who similarly report varying outcomes based on education and identify a glass ceiling effect for highly educated women in Spain and for young highly educated women in Italy's Venetian region.

7. Conclusions and policy recommendations

The study investigates the gender pay gap in Kenya, emphasizing the significant role of education in shaping earnings disparities. It contributes to the literature on gender earnings differentials by employing a distributional approach, using quantile regression techniques to control for various covariates at different points in the earnings distribution. The *Machado and Mata (2005)* decomposition method is applied to break down the gender pay gap at each decile into components related to differences in earnings structures and individual productive characteristics. Additionally, counterfactual gender earnings gaps were generated to estimate what the gap would be if women retained their productive characteristics but were compensated like men. The analysis is based on data from the *Kenya Continuous Household Survey (2021)* data.

Present study reveals several key findings. Gender pay differentials in Kenya are strongly influenced by educational attainment: low-educated women face significantly larger pay penalties, particularly in the median quantiles of the earnings distribution, while highly educated women experience relatively smaller earnings gaps that are more pronounced at the top of the distribution. After controlling for nonrandom sample selection, the earnings loss for women relative to men ranges from 8.3 to 28.9% for highly educated workers and from 24.9 to 66.7% for low-educated workers. Additionally, the trend of the gap varies between the two groups: highly educated women reduce the gap at the lower end but lose this advantage at higher earnings levels, whereas low-educated women exhibit a more pronounced gap in the median quantiles. Regarding the presence of a glass ceiling or sticky floor effect, the analysis identifies a persistent glass ceiling effect for highly educated women. In contrast, a sticky floor pattern is observed for low-educated women, particularly at the 4th decile, indicating that low-educated women are more positively selected into low-paying occupations compared to men.

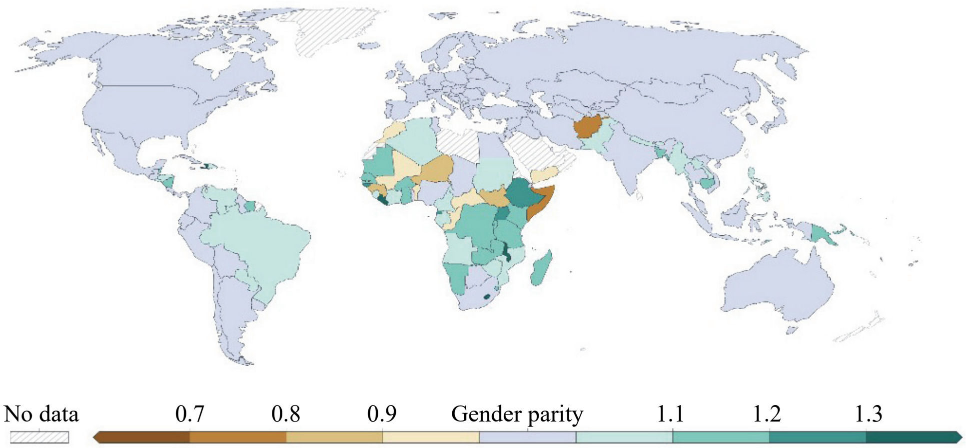
For low-educated workers, even if men and women shared the same characteristics, women would still face significant earnings penalties, except at the lower end of the distribution. The pay gap, driven by differences in returns to endowments, favors men and it is most pronounced at the bottom of the earnings distribution. If men and women had identical characteristics among highly educated workers, women would still experience earnings penalties, though this effect is statistically insignificant across the distribution. Here, the wage gap also favors men, particularly at the top of the distribution. The primary driver of the gender pay gap among highly educated workers is the differences in returns to productivity-related characteristics, representing the unexplained component associated with discriminatory practices and other unobservable factors in the labor market. Additionally, counterfactual distributions reveal that the pay gap would favor women among highly educated individuals, with this effect being more significant for high-wage earners. For low-educated workers, the gap would similarly favor women across the entire earnings distribution. These results in the Kenyan labor market can be attributed to a combination of structural inequalities, occupational segregation, and discriminatory practices. This underscores the need for policies addressing occupational segregation, discriminatory wage practices, and barriers to high-paying positions, particularly for low-educated women at the lower and median earnings levels and highly educated women at the top of the distribution.

These findings suggest that achieving equitable labor market outcomes for African men and women require significant efforts to strengthen the enforcement of gender-neutral labor market regulations within Kenyan labor legislation. Mitigatory measures should particularly target low-educated women at the lower and median levels of the earnings distribution, as they are most vulnerable to horizontal occupational segregation. For low-educated women, fight horizontal occupational segregation by promoting vocational training and access to higher-paying sectors, alongside enforcing equal pay audits and transparency to reduce discrimination in returns to productivity-related endowments. For highly educated women**,** end the „glass ceiling" through mentorship programs, leadership training, and strict enforcement of anti-discrimination laws in high-paying roles. Additionally, the mitigatory measures includes upskilling initiatives to enhance human capital for low-educated women and incentivize firms to hire/promote women in senior positions. Addressing systemic undervaluation of women's productivity by revising earnings structures and conducting regular pay equity reviews. Strengthening labor laws to penalize discriminatory practices. Lastly, collaborate with stakeholders (government, NGOs, private sector) to fund programs and monitor outcomes, ensuring policies adapt to evolving labor market dynamics.

Appendix

Figure A1

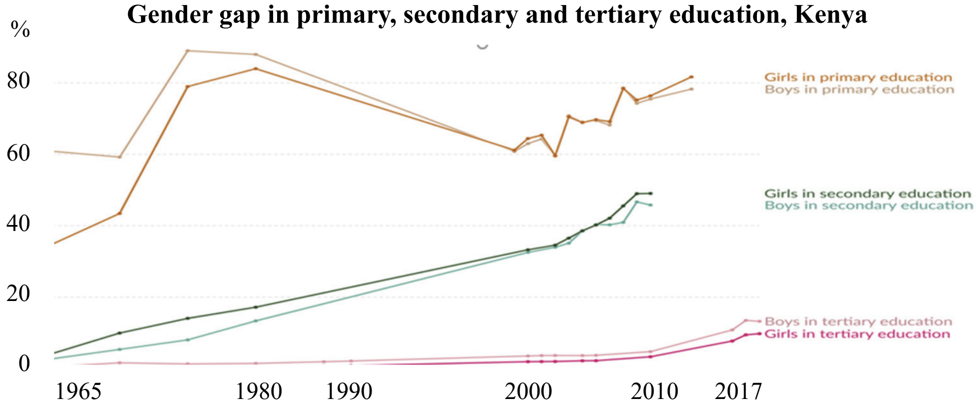
Primary school completion rates, adjusted gender parity index, 2024



Notes: 1) An adjusted gender parity index of 1 indicates equal primary school completion rates of both females and males. A value smaller than 1 indicates disparity in favor of males and a value greater than 1 indicates disparity in favor of females. Gender parity is defined as a GPI between 0.97 and 1.03. Values below 0.97 favor males, and above 1 favor females. 2) Adjusted gender parity index (GPI) is calculated by dividing the female indicator value by the male value. To ensure symmetry around 1, when the ratio is greater than 1, the adjusted GPI is calculated as the ratio of male to female values and the ratio is subtracted from 2. 3) Primary education (International Standard Classification of Education Level 1) aims to impart fundamental literacy and numeracy skills while providing a solid foundation in key knowledge areas and personal and social development, serving as preparation for lower-secondary education with a focus on basic-level learning and minimal specialization.

Figure A2

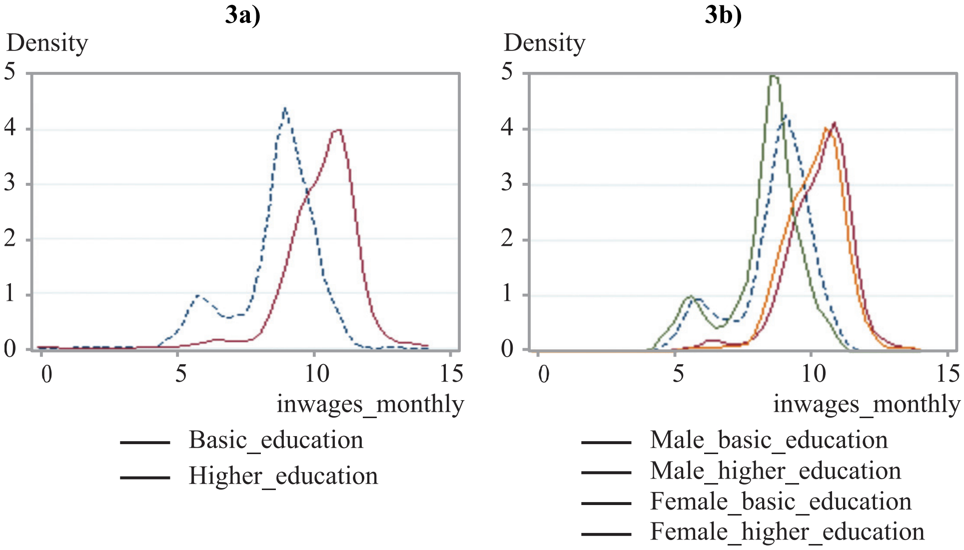
Gender gap in primary, secondary and tertiary education, Kenya



Notes: Share of boys or girls within the relevant age group enrolled in primary, secondary, and tertiary education. 1) Primary education (International Standard Classification of Education Level 1) aims to impart fundamental literacy and numeracy skills while providing a solid foundation in key knowledge areas and personal and social development, serving as preparation for lower-secondary education with a focus on basic-level learning and minimal specialization. 2) Secondary education (International Standard Classification of Education Level 2 and 3) completes the provision of basic education that began at the primary education level and aims at laying the foundation of lifelong learning and human development by offering more subject- or skill-oriented instructions using more specialized teachers. 3) Tertiary education (International Standard Classification of Education Level 5 and 8) expands upon secondary education by offering specialized learning activities in various fields. It targets advanced levels of complexity and specialization, encompassing both academic and vocational or professional education. Source: Multiple Sources Compiled by *UNESCO Institute for Statistics (2025)*.

Figure A3

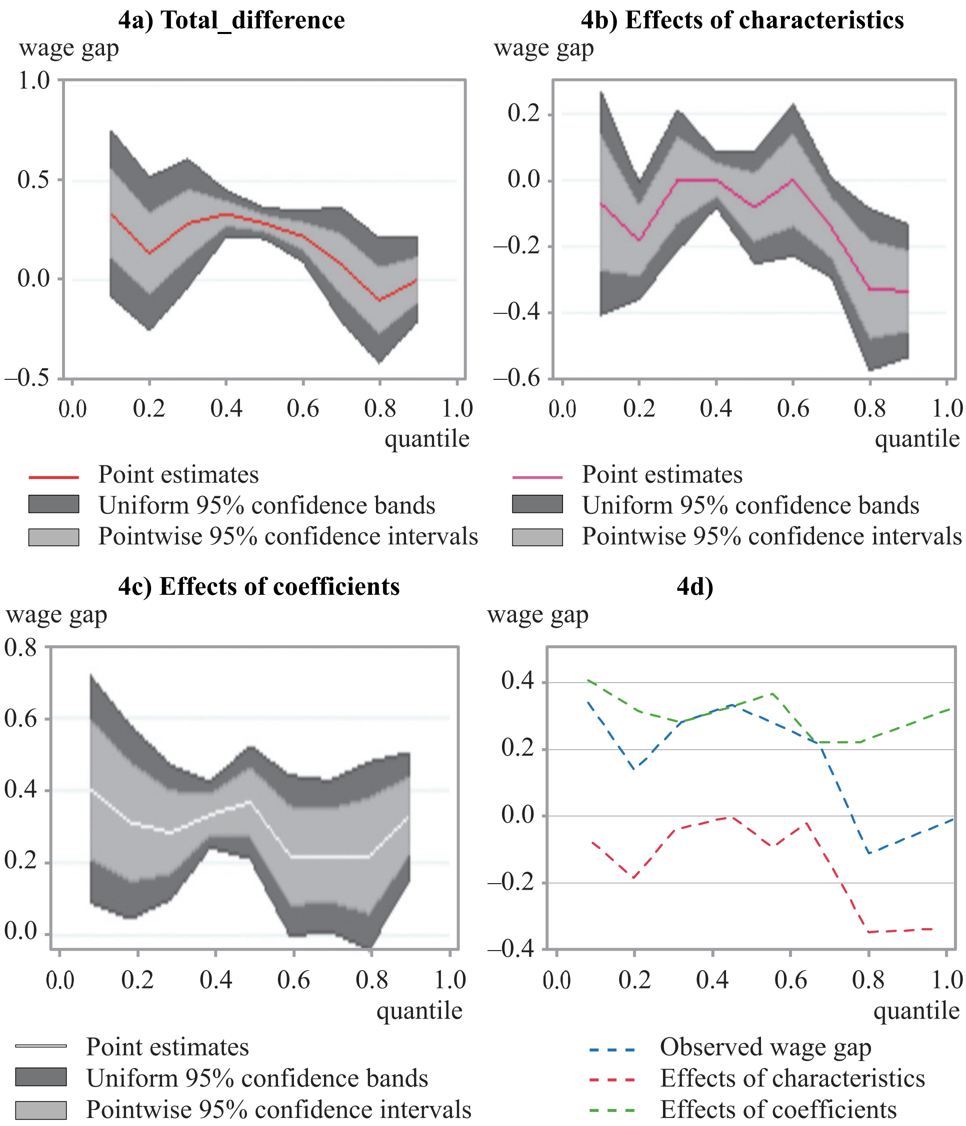
Kernel density plot of earnings distribution by gender and education level



Note: individuals aged 15 and 65 years. Monthly earnings in Kenya shillings (Ksh).
Source: author's calculations based on *KCHS (2021)* data.

Figure A4

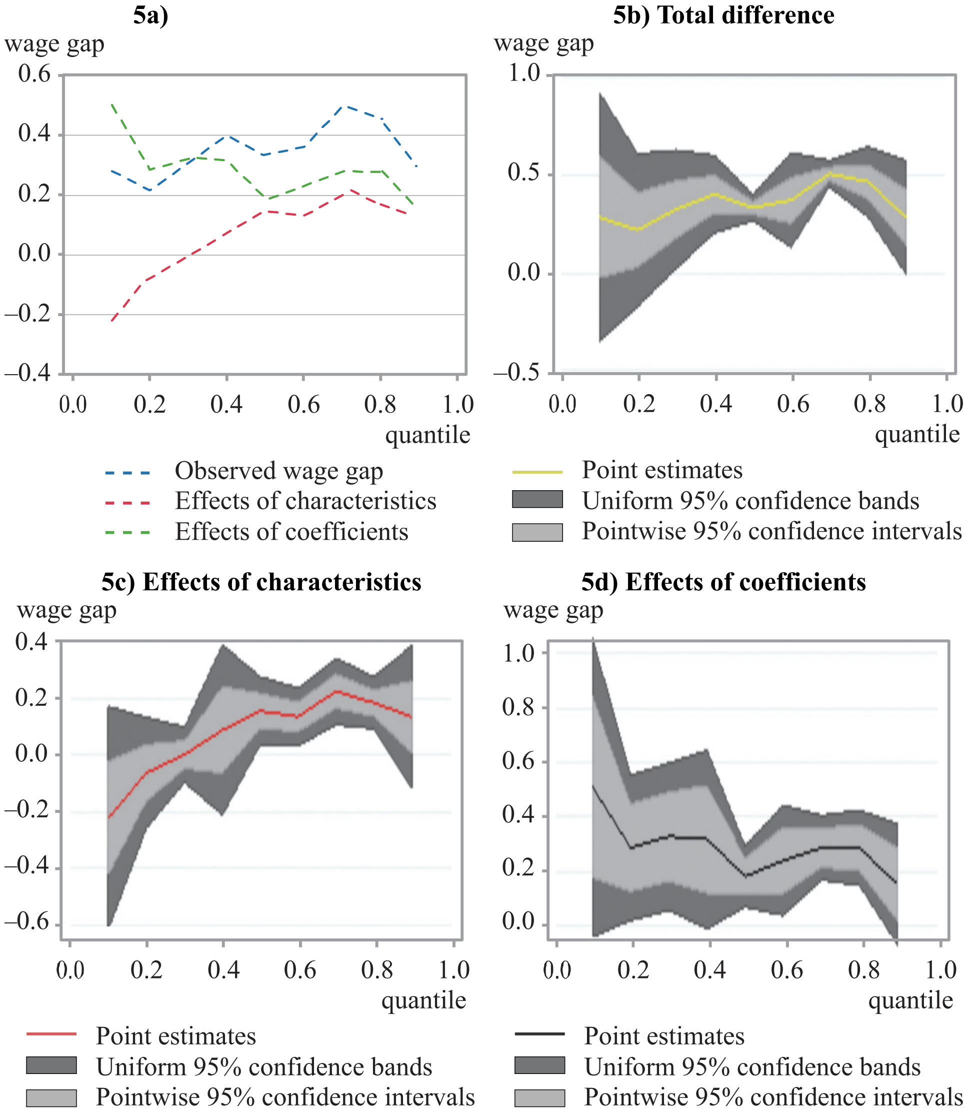
Decomposition of gender pay gap – whole sample



Note: bootstrapping using 100 replications.
Source: author's calculations based on *KCHS (2021)* data.

Figure A5

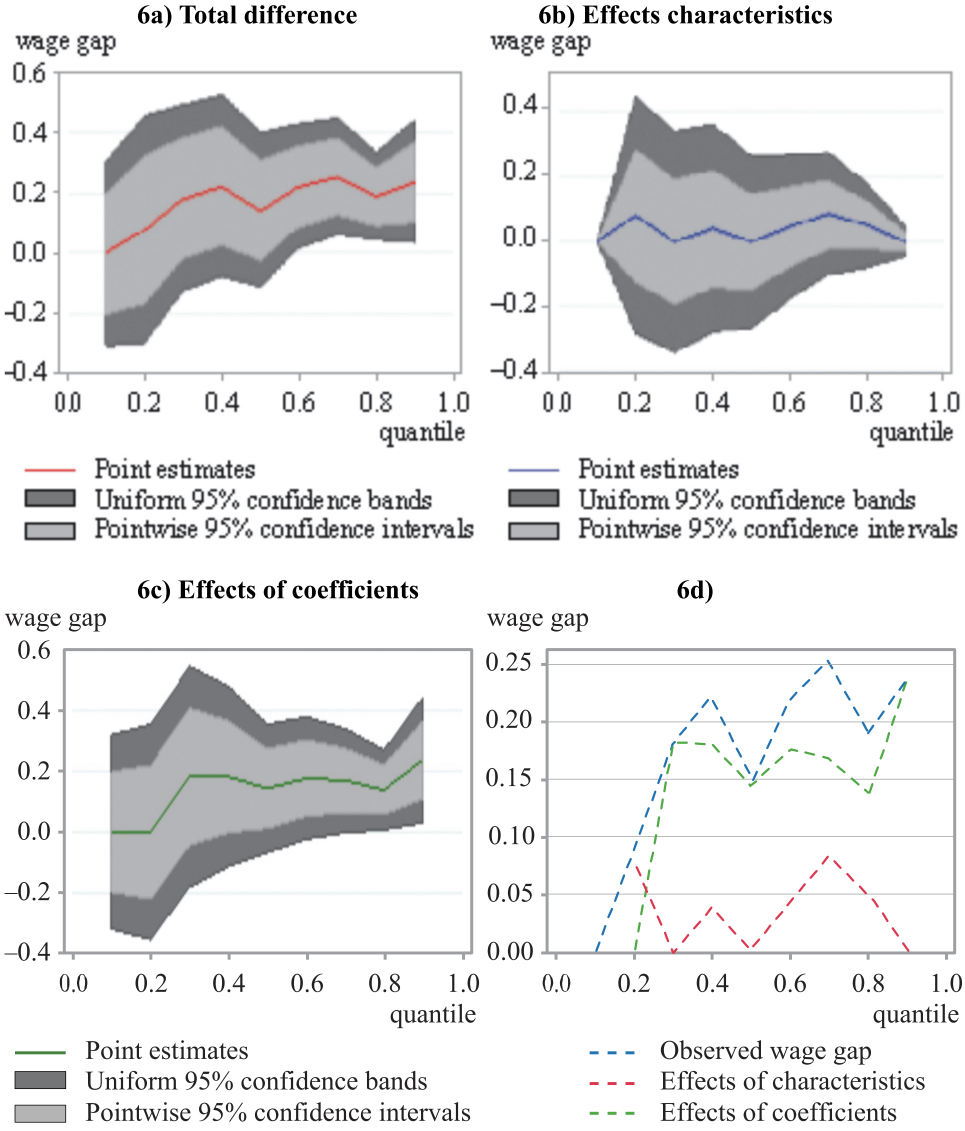
Decomposition of gender pay gap for low-educated workers



Note: bootstrapping using 100 replications.
Source: author's calculations based on *KCHS (2021)* data.

Figure A6

Decomposition of gender pay gap for highly educated workers



Note: bootstrapping using 100 replications.
Source: author's calculations based on *KCHS (2021)* data.

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