PHD DISSERTATION

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Szeged, 2025

UNIVERSITY OF SZEGED

FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION
DOCTORAL SCHOOL IN ECONOMICS

THE UTOPIA OF THE KENYAN LABOR MARKET: A DECOMPOSITION ANALYSIS OF GENDER PAY GAPS AND OCCUPATIONAL SEGREGATION

PhD Dissertation

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DECLARATION AND APPROVAL

Candidate's Declaration

I hereby declare that every section and component of this PhD thesis represents my original work, and it has not been previously submitted, presented, or used to obtain any diploma, degree, or academic qualification at this university or any other institution of higher learning. All references to books, journal articles, and organizational websites have been appropriately cited within the text and accurately listed in the references.

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Supervisor's Approval

This confirms that the PhD candidate carried out the research presented in this thesis under our supervision and guidance. Accordingly, the thesis has been thoroughly reviewed, approved, and submitted with our approval as the candidate's supervisors.

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DEDICATION

I dedicate this thesis to several important individuals in my life. First, I want to honor my late Aunt Rudisa, who passed away while I was studying abroad. Despite our physical distance, we maintained a close connection through video calls, and I did my best to care for her. Unfortunately, I did not have the opportunity to give her a proper farewell, but I will live to carry on the love she had for all of us. Second, I dedicate this work to my beloved late cousin, Mr. Fredrick Mukhayi, who was like a brother to me. He left us at a time when we were striving to raise our family from abject poverty. To the two sons he left behind, I now take on the role of a father figure. Lastly, I dedicate this thesis to all first-born sons in African families. The story of an African first-born child reflects the sacrifices we make for our siblings and families to break the cycle of generational poverty. The parental responsibilities we assume at a young age to shape our familial futures come with a significant personal cost. We are often like the captain of a ship, guiding a whole generation that looks up to us.

ACKNOWLEDGEMENT

I begin by honoring my own journey—the resilience that carried me through this PhD, especially as a first-born son who shouldered familial duties early in life. Balancing parental responsibilities for my siblings with academic ambitions demanded immense sacrifice, but perseverance prevailed. This milestone is a testament to relentless effort and self-belief, thanks to me. Next, my deepest gratitude goes to my supervisors, Dr. Judit Gébert and Prof. György Málovics, whose mentorship transcended academia. Their unwavering support during conferences, funding applications, and rigorous research phases, coupled with their trust in my autonomy, shaped this work profoundly. To my parents, Joseph Abwoga Alwago and Grace Mukhayi Ogusinin: you shattered societal barriers and poverty's grip to create my path. To my six siblings, your prayers strengthened me. To my son, Ashton, and nephew, Joe—your smiles, even just via video calls, reminded me of life's brightest joys.

I also extend heartfelt thanks to the University of Szeged's Faculty of Economics and Business Administration leadership: Dr. Benedek Nagy (The Dean), Prof. Beata Farkas (Head of Doctoral School in Economics), and faculty members Prof. Miklós Szany, Associate professors: Dr. Izabella Szakálné Kanó, Dr. Zsófia Vas, Dr. Gábor Kiss, and Assistant professors: Dr. Marianna Sávai, Dr. Eva Kuruczleki, Dr. Balázs Tóth, whose academic guidance and personal camaraderie enriched my journey. The Hungarian Government, via the Stipendium Hungaricum Scholarship, granted me a life-altering opportunity—a beacon of educational equity.

To my PhD peers at Szeged—Dr. Timothy Yaw, Dr. Senanu Klutse, Dr. Gabriel Temesgen, Dr. Ibrahim, Dr. Bishop Sarkodie, Mr. Kobla, Mr. Elyor, Mr. Michael Asiamah, and Dr. Maket Juma Isaiah (a brother-in-dreams-turned-reality)—your insights and solidarity were invaluable. My classmates Mrs. Andi Sri Wahyuni, Mr. Mahammad, Miss Mansiya, Miss Chintana, and Miss Stacey-Lee Marais: thank you for blending rigor with camaraderie. I also extend my heartfelt gratitude to the United Nations University World Institute of Development Economics Research (UNU-WIDER) for providing financial support through the PhD Fellowship in Helsinki, Finland. Special thanks to my fellow UNU-WIDER PhD Fellows—Samira, Alexandra, Martin, Basit, Evegyniya, and Krishna—for their camaraderie and support throughout this journey. The UNU-WIDER fellowship transformed my research into notable publications and opened doors to my participation in global forums like the United Nations Economist Network (UNEN) HLPF in New

York and the Sustainable Development Transformation Forum (SDTF) in Incheon, Republic of Korea. My UNU-WIDER mentors—Amina Ebrahim, Kwabena Adu-Ababio, Prof. Kunal Sen (Director UNU-WIDER), Dr. Abrams Tagem, Dr. Richard Kima, Dr. Rodrigo Oliveira, Prof Michael Danquah, and Prof. Williams Ohemeng and others—deserve special recognition. Similarly, African Social Research—PASIRI's Lusaka, Zambia research workshop catalyzed another pivotal publication and provided financial support.

Finally, my eternal gratitude to God, whose wisdom illuminated my darkest hours and steered this journey to fruition. All glory rests in divine guidance.

LIST OF PUBLICATIONS

Peer-Revered Journal Papers

1. Alwago, W.O., (2022). Is the Renminbi a Global Currency in the Making? Globalization of Digital yuan. *PÉNZÜGYI SZEMLE/PUBLIC FINANCE QUARTERLY*, *67*(4), pp.553-566: https://doi.org/10.35551/PFQ_2022_4_5
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11. Gender Pay Gap by Education Stratification in Kenya. *Hungarian Statistical Review* (Under Review).
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1. **Alwago, W.O., 2024**. A partial least squares analysis of gender inequality, occupational segregation, and economic growth: Evidence from Sub-Saharan Africa. 2024 Sustainable Development Transformation Forum (SDTF) 29-31 October 2024, Incheon, Republic of Korea.
2. **Alwago, W.O., 2024.** Why women earn less: The role of occupational segregation in Kenya's gender pay differential. Program on African Social Research's (PASR) Junior Scholars' Workshop in Lusaka, Zambia, on August 14th and 15th, 2024.
3. **Alwago, W.O., 2024.** Why women earn less: The role of occupational and Industrial segregation in Kenya's gender pay differential. UNU-WIDER Visiting PhD Fellow Workshop in Helsinki, Finland, on 27TH June 2024.
4. **Alwago, W.O 2024.** The Quest for education parity in addressing gender wage differentials. Globalisation, integration, cooperation – What is at stake in the current turbulent times? 22-23 March 2024, Szeged, Hungary.
5. **Alwago, W.O., 2023.** Gender wage gap in the urban labor market of Kenya. 2023 Income and wealth inequality: Drivers and consequences Conference, September 27-29, 2023, Gdańsk, Poland.
6. **Alwago, W.O., 2023.** Gender labor market outcomes during the COVID-19 pandemic: Evidence of she-cession in the Visegrád countries. Decades of crises: from competitiveness to resilience-via the bumpy road to sustainability. The fifth conference in cooperation with the European Association for Comparative Economic Studies, 14-15 April 2023, Szeged, Hungary.
7. **Alwago, W.O., 2022.** The nexus between health expenditure, life expectancy, and economic growth: An ARDL model analysis for Kenya. The international conference on Economy-History-Society, second edition, on 24-25 November 2022, Satu Mare, Romania.

8. **Alwago, W.O., 2023.** The impact of environmental taxation on carbon dioxide emissions in Romania: An ARDL linked cointegration approach. XXXIII Edition of Arad Academic Days, 23-27 May 2023, Arad, Romania.
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11. **Alwago, W.O., 2023**. Gender labor market outcomes during the COVID-19 pandemic: Evidence of she-cession in the Visegrád countries. The International Conference Regional Sustainable Development Through Competitiveness, Innovation and Human capital, held on 25-27th October 2023, in Baia Mare, Romania.

ABSTRACT

As the midpoint of the 2030 Agenda, global efforts to achieve the 17 Sustainable Development Goals are dangerously off course. The 2024 SDGs Report states that just 17% of targets are progressing as planned, with nearly half making only limited or moderate headway, and over one-third stagnating or regressing. Within this context, gender inequality (SDG#5) in labor markets persists as a critical and enduring barrier to sustainable development. To fulfill SDGs#5 and #8 and advance the Africa Agenda 2063 ("*the Africa we want*"), Sub-Saharan Africa—and Kenya in particular—must urgently address pervasive gender disparities. These inequities directly contradict the vision of a utopian Kenyan society: one that guarantees gender parity in all opportunities.

This thesis weaves together three interrelated studies to comprehensively analyze gender-based earnings disparities and occupational segregation in Kenya's labor market. The first empirical study investigates the sources and magnitude of the gender pay gap across Kenya's formal (public and private) and informal sectors, as well as between distinct age cohorts (15–34 years versus 35+ years). The second empirical study examines how education stratification—specifically the dichotomy between highly educated and low-educated workers—shapes divergent patterns in gender pay gaps. The third study evaluates the role of occupational and industrial segregation in perpetuating gender-based earnings inequalities, probing how gender distributions across occupations reinforce systemic inequities. Guided by human capital theory and labor market segmentation/discrimination frameworks, the thesis seeks to uncover the structural and institutional drivers of these disparities. Central to all three studies is the use of nationally representative data taken from the 2021 Kenya Continuous Household Survey, which encompasses 17,042 households and 68,677 individuals**,** ensuring robust empirical grounding.

In Chapter Five, the thesis presents descriptive statistics from the three empirical studies. The findings indicate that women generally experience less favorable employment outcomes than men, with lower overall employment rates for women. The descriptives reveal significant gender disparities in Kenya's labor market, shaped by employment sectors, education, and structural inequalities. Women face lower employment rates (73.56% vs. 80.40% for men) and they are disproportionately engaged in unpaid home labor (12% of women vs. 5% of men), reflecting entrenched gender roles. Wage employment is dominated by the informal sector (73.1% of men

and 65.1% of women), with men more likely to secure formal roles in public or private sectors. While women have a higher educational attainment at advanced levels, a persistent gap favors men with bachelor's degrees, particularly among younger cohorts. Occupational segregation is stark: highly educated women are more likely to hold professional roles (61% vs. 44% of men), but low-educated individuals—especially women—are relegated to low-skilled jobs (only 4.5% of low-educated women work as professionals).

Chapter Six examines the first thesis objective, testing the hypothesis that gender earnings disparities stem primarily from human capital determinants, with significant variations across employment sectors and age cohorts. The analysis utilizes data taken from KCHS–2021, divided into two age groups (15–34 years: 3,414 workers; 35–65 years: 3,239 workers) and sectors of employment: public (1,229 waged workers), private formal (747 waged workers), and informal sectors (4.677 waged workers). To address endogeneity and selection bias in wage employment and sectoral choice, earnings equations are estimated using OLS, BFG, and Heckman selection models**.** The gender pay gap is decomposed based on the reweighted Oaxaca-RIF decomposition technique, chosen for its robustness in isolating structural and composition effects.

The findings confirm that women earn significantly less than men, with the gender pay gap most pronounced in the informal sector—especially the informal economy, where women earn 41.8% less than men—compared to a narrower 6.4% gap in the public sector and 8.1% in the private formal sector. While the public sector exhibits relative progress through standardized pay scales and affirmative action, the systemic undervaluation of women's productivity persists, driven by structural inequities and discriminatory practices. Age further stratifies the gender pay gap: Older workers (35+ years) experience a gap of 16.6%, nearly double that of younger cohorts (9.5%). Older women, despite accumulating better productivity characteristics over time, face cumulative discrimination, including occupational segregation into informal caregiving and unequal returns to experience. Younger women, though encountering a narrower gap, grapple with emerging barriers like gig economy precarity and skills mismatches, compounded by childcare responsibilities and limited access to vocational training.

As expected, the human capital elements significantly explains these disparities. Education, a key component, reduces the gender pay gap via composition effects, as women increasingly match or surpass men in educational attainment due to government-led gender equity initiatives. However, these gains are undermined by wage structural effects—discriminatory returns to productivity traits—which dominate the gender pay gap, accounting for 70.1% to 113.4% of the gap. This highlights the systemic undervaluation of women's productivity traits and observable qualifications, aligning with labor market discrimination theories—such as statistical and taste-based discrimination. While wage structural effects are more pronounced in the informal sector, their significant presence in the public sector underscores institutional biases favoring men, particularly in senior leadership roles often tied to political appointments that predominantly benefit male employees. The informal sector's structural effects peak at higher deciles, highlighting unregulated working conditions and absent collective bargaining, trapping women in low-productivity roles like agriculture and domestic work with minimal social protection. In the private formal sector, wage structural biases at lower deciles result in a "*sticky floor*" effect, reflecting employer discretion and cyclical wage discrimination. Conversely, the public sector's institutional frameworks mitigate these wage structural effects but fail to address biases due to structural factors. Demographic factors—such as marital status and regional disparities—and job-related attributes like firm size and union affiliation further entrench gender inequities in Kenya's labor market.

In Chapter Seven, I analyzed the second objective, exploring how educational attainment shapes distinct barriers for women in Kenya's labor market. The analysis assumed that highly educated women confront systemic barriers akin to a "*glass ceiling*"**,** limiting their earnings potential while low-educated women remain trapped in a "*sticky floor*" of low-wage. To test this, the study utilized data from 1,500 highly educated and 5,153 low-educated workers, applying the Machado and Mata decomposition to dissect gender pay gaps across the entire earnings distribution. For low-educated women, the findings painted a stark picture of structural inequity. Their earnings lagged behind men's by 25% to 66.7%**,** with the widest gaps at median income levels. This "*sticky floor*" effect stemmed from systemic undervaluation of their productivity traits, compounded by their overrepresentation in Kenya's informal economy—81% of non-agricultural jobs—where roles in retail, domestic work, and small-scale agriculture lack wage standardization, union protections (only 3.7% coverage), and labor rights. However, a modest narrowing at upper deciles suggests that Kenya's minimum wage policies and union advocacy offer a limited respite.

Highly educated women, though better placed, faced a contrasting challenge: a "*glass ceiling*" most pronounced at the 70th percentile of earnings distribution. Despite holding 50% of managerial roles, vertical segregation in sectors like education and public administration persisted, with cultural biases and discriminatory promotion practices stifling advancement. Even with identical qualifications, women earned 8.3–28.9% less than men, a disparity exacerbated by gendered returns to industrial choices and men's higher average work experience. These findings underscore how formal sectors, while offering better opportunities, remain rife with institutionalized inequities.

In Chapter Eight, I explore the role of occupational and industrial segregation in driving gender pay disparities in Kenya, testing the hypothesis that occupational status and structures significantly account for the gender pay gap**.** To investigate this, the KCHS-2021 data is divided into 2,903 urban workers and 3,750 rural workers, and the BMZ decomposition method is applied. The Duncan dissimilarity index reveals that achieving gender-equitable employment distribution would require approximately 37% of women (men) to change occupations**,** 9% to shift sectors, and 30% to switch industries. If Kenyan women (men) had parity in occupational opportunities and choices, a significant shift toward higher-paying roles—such as legislators, managers, professionals, associate professionals, technicians, service and sales workers, and clerical positions—would most likely occur. However, women remain underrepresented in these sectors, a disparity attributed to systemic biases and unobserved barriers restricting their access. Conversely, women are disproportionately overrepresented in low-paying occupations, including skilled agriculture, forestry, fishery, and elementary roles. These findings underscore the significant role of structural segregation in perpetuating gender pay differentials.

The decomposition results reveals that *intra-occupation* disparities—driven by unequal returns to productivity characteristics and occupational structures between men and women—account for largest portion of the gender pay gap, highlighting pervasive vertical segregation. Rural areas exhibit a pronounced GPG of 27.9%, nearly nine times higher than urban areas (2.9%). This rural-urban chasm stems from Kenya's informal economy, where non-agricultural and agricultural workers lack formal protections. Rural women are concentrated in low-productivity sectors like subsistence farming and elementary occupations, where earnings are unregulated and labor protections virtually absent. The results mean that based on observable productivity characteristics (e.g., education, experience), the rural GPG could theoretically be eliminated, but the overwhelming "*unexplained*" component reflecting entrenched earnings discrimination and vertical segregation within occupations, perpetuates the GPG. In other words, if women's average productivity traits were equally rewarded as men's, the gender pay gap would be eliminated. However, the gap widens when considering the returns to these observable characteristics and the occupational distribution of men and women, accounting for 403% of the total GPG in rural areas. This highlights the systemic undervaluation of women's productivity in Kenya's rural labor market.

In urban areas, while the gender pay gap is narrower (2.9%), the results reveal persistent vertical segregation within occupations. Women in urban areas seem to exhibit superior productivity-related characteristics *within—and across—occupations*. Observable factors reduce the GPG more significantly in rural areas (-306%) than in urban regions (-136%). In contrast, the impact of returns to these factors and occupational structures is less pronounced in urban areas compared to rural areas. Urban areas have a negative *inter-occupation* unexplained component, indicating fewer barriers for women accessing higher-paying jobs. However, the positive *intra-occupation* unexplained component in both regions points to wage structural effects and vertical occupational segregation as key drivers of pay disparities. While urban women are concentrated in better-remunerated occupations (evidenced by a *negative inter-occupation* unexplained component), they potentially face barriers in high-paying roles like STEM occupations.

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LIST OF ACRONYMS AND ABBREVIATIONS

BFG:	Bourguignon, Fourier, and Gurgand
BMZ:	Brown-Moon-Zoloth
CEDAW:	Convention on the Elimination of All Forms of Discrimination Against Women
GPG:	Gender Pay Gap
ILO:	International Labor Organization
ISCO:	International Standard Classification of Occupations
ISCED:	International Standard Classification of Education
KeSCO:	Kenya Standard Classification of Occupations
KCHS:	Kenya Continuous Household Survey
KNBS:	Kenya National Bureau of Statistics
MDGs:	Millennium Development Goals
O-B:	Oaxaca and Blinder
OECD:	Organization of Economic Co-operation and Development
OLS:	Ordinary Least Square
RIF:	Recentered Influence Function
SDGs:	Sustainable Development Goals
SSA:	Sub-Saharan Africa
STEM:	Science, Technology, Engineering, and Mathematics
TVET:	Technical and Vocational Education and Training
UN:	United Nations
UNDP:	United Nations Development Programme
WEF:	World Economic Forum

1. INTRODUCTION

The rationale for this thesis on gender pay gaps in the Kenyan labor market stems from the recognition that gender inequality is a significant global concern with far-reaching gender imbalance labor market outcomes. Here, I define the scope of the thesis by discussing the rationale, motivation, actuality, and justification of the research. I provide background information that identifies the existing research concern. Furthermore, I outline the research objectives, hypotheses, and questions. Then I describe the structure and organization of the dissertation.

1.1 Background and Motivation

Gender inequality—the systemic disparity in treatment and opportunities afforded to individuals based on gender—remains a persistent challenge in labor markets worldwide, with profound implications for human rights and socioeconomic progress. Recognized as both a fundamental human right and a foundational pillar of economic development, gender equality enhances macroeconomic efficiency and alleviates poverty (World Bank, 2011; Robles, 2012; Barnat et al., 2020). International frameworks, such as the United Nations [UN] Charter (1945) and the Universal Declaration of Human Rights (1948), enshrine principles of equality and non-discrimination, affirming the rights of all individuals irrespective of gender. Building on these principles, the UN (1979) Convention on the Elimination of All Forms of Discrimination Against Women explicitly targeted gender-based discrimination and provided a legal mandate for nations to dismantle structural barriers to equality. Despite these commitments, women's labor market outcomes remained systematically marginalized (U.N., 1995). The Beijing Declaration and Platform for Action (U.N., 1995) emphasized this oversight, highlighting the necessity of targeted legal and policy interventions to address entrenched inequities.

The Millennium Development Goals [MDGs], established in 2000, prioritized gender equality through their third objective: "promoting gender equality and empowering women." While the economic gap between men and women narrowed considerably in the late 20th century, persistent disparities in employment, wages, and domestic labor duties underscore ongoing inequalities (Ponthieux & Meurs, 2015). The MDG progress report highlighted advancements in educational parity, economic participation, and political representation for women (UN, 2015a). Nevertheless, in Sub-Saharan Africa [SSA], women continue to face systemic marginalization in formal employment, enduring significant wage gaps, overrepresentation in part-time roles, and disproportionate responsibility for unpaid care work (UN, 2015b; Ponthieux & Meurs, 2015). To speed things up, the UN General Assembly launched UN Women in 2010, consolidating global efforts toward gender equality (UN Women, 2018). In parallel, the International Labor Organization [ILO] established four core conventions addressing gender inequities: the Equal Remuneration Convention (No. 100), the Discrimination (Employment and Occupation) Convention (No. 111), the Workers with Family Responsibilities Convention (No. 156), and the Maternity Protection Convention (No. 183). Most SSA nations, among other things, ratified key frameworks such as Conventions No. 100 and 111, signaling formal commitment to equitable labor practices (Robles, 2012).

Despite the widespread ratification of UN and ILO conventions by most SSA countries, persistent challenges in implementation and enforcement undermine their effectiveness. Entrenched traditional, customary, and religious norms across SSA continue to impede the adoption of international labor standards and hinder progress toward gender equality and women's empowerment. Societal expectations often coerce women into conforming to culturally sanctioned roles, prompting them to opt for occupations perceived as compatible with reproductive and caregiving duties. This societal expectations perpetuates their overrepresentation in informal, low job security sectors characterized by low wages and unfavorable working conditions compared to formal employment (World Bank, 2011). The Addis Ababa Action Agenda emphasized that gender inclusivity—especially in social, economic, and political domains—is indispensable for achieving the Sustainable Development Goals [SDGs] and fostering equitable economic growth (UN, 2015c). Complementing this, the 2030 Agenda prioritizes gender equality more assertively, explicitly seeking to eradicate all forms of discrimination and violence against women (UN, 2015d).

The global increase in women's labor force participation is widely recognized in the literature as one of the most transformative social shifts of the 20th century. Goldin (2006) attributes this shift to three pivotal changes in women's lives: evolving *horizons* (long-term career aspirations), *identity* (professional self-conception), and *decision-making autonomy* (control over work-life balance). The most profound transition occurred as women advanced professionalism, gained independence in managing their time irrespective of spousal employment choices, and shifted from temporary employment to sustained, stable career trajectories (Petrillo, 2022). In

OECD countries, for instance, female labor force participation jumped from under 52% in 1980 to a record 64% in 2022 (OECD, 2022c). However, this trend has not been mirrored in developing regions. In SSA, female participation rates have remained constant at about 60% since the 1990s—a figure that, while 14 percentage points above the global average (ILO, 2021), reflects persistent structural barriers to equitable labor market integration.

Long-term labor market engagement has motivated women to turn to investments in human capital through formal education and on-the-job training (Bratti, 2001). By 1980, women in both developed and developing nations had matched or surpassed men in tertiary education attainment (Blau & Kahn, 2017). OECD (2023) figures assert that women now surpass men in tertiary degree completion across member states: 42% of women aged 25–64 hold such qualifications, compared to 35% of men. While SSA has narrowed gender gaps in primary and secondary education, parity in tertiary graduation remains elusive, with only 65 women graduating for every 100 men in 2019. In contrast, North Africa reports higher female tertiary graduation rates than male (Kouassi & Jakkie, 2024). And despite strides in universal education access, girls remain underrepresented in technical and vocational education [TVET] and STEM programs, perpetuating sectoral imbalances (African Development Bank, 2023).

Scholars have extensively evaluated the marked progress in women's labor market outcomes, attributing these gains to policy reforms, human capital investments, and shifting occupational dynamics (Goldin & Katz, 2002; DiPrete & Buchmann, 2006; Nicoletti et al., 2018). Critical to this advancement has been the adoption of anti-discrimination legislation, such as Kenya's Employment Act of 2007, which mandates equal pay for work of equal value within the same occupation and sector (Republic of Kenya, 2021). Complementary policies intended to reconcile motherhood and career advancement—including subsidized childcare and parental leave—have further mitigated gender disparities by reducing childbearing-related opportunity costs (Del Boca & Locatelli, 2006). At the same time, women's expanded investment in education and training has diminished, though not eradicated, occupational segregation. Historically concentrated in administrative support and service roles prior to 1970, women have since made substantial inroads into traditionally male-dominated sectors such as management and technical professions (Blau & Kahn, 2017).

Globally, *The Global Gender Gap Report 2023* (World Economic Forum [WEF], 2023) reports a Global Gender Gap Index[1] score of 68.4% in 2023, marking a marginal 0.3 percentage-point improvement from 2022 and leaving a 31.6% disparity. Progress toward gender parity has been sluggish, with only a 4.1 percentage-point increase since 2006. At this pace, achieving full parity will require 131 years, far exceeding the 100-year projection made in 2020 (WEF, 2023). While global parity scores have fallen to pre-pandemic levels, the deceleration of progress highlights the lingering effects of the COVID-19 crisis. Research highlights a pronounced "*she-cession*," wherein women's employment and economic security were disproportionately eroded by the pandemic (Alon et al., 2020; Madgavkar et al., 2020; Dang & Nguyen, 2021; Alwago, 2023). Key factors include: (1) women's overrepresentation in lockdown-sensitive sectors (e.g., hospitality, retail); (2) steeper and earlier declines in female labor force participation compared to men; (3) the disproportionate absorption of increased unpaid caregiving duties, exacerbated by childcare facilities closures; and (4) slower rates of re-employment post-crisis.

Despite significant progress in addressing gender inequalities in labor markets over recent decades, disparities persist globally. A critical concern remains the gender pay gap [GPG]—defined as differences in average gross earnings between men and women within the same occupation, industry, and role (Metcalf, 2009)—which continues to challenge both developed and developing economies (Blau & Kahn, 2017). Empirical studies consistently demonstrate that men outearn women even after controlling for observable productivity-related factors and wage structures (Firpo et al., 2018). Economic theories blame this disparity on two primary drivers: *qualifications* and *discrimination*. The human capital model asserts that earnings reflect the skills and competencies acquired through education, training, and experience, with higher qualifications correlating to greater returns for both genders (*see* Becker, 1957, 1964; Reich et al., 1973). While women's educational attainment has risen markedly in recent decades (Botsch, 2015), their investments in human capital have not translated into commensurate earnings relative to men, underscoring systemic inequities in labor market rewards.

Work experience, another pivotal component of the human capital model, plays a central role in perpetuating gender-based earnings disparities (Sierminska et al., 2010). While experience

[1] The Global Gender Gap Index was introduced in 2006 by the World Economic Forum and it takes into consideration many dimensions of gender disparities including economic participation, education attainment, health, and political empowerment.

enhances earnings for both genders, women's career trajectories are often shaped by anticipated caregiving responsibilities, leading to shorter and more fragmented labor market participation compared to men (Polachek, 1981). To mitigate penalties from career interruptions, women frequently self-select into occupations with greater flexibility but lower wage growth (Botsch, 2015; Ponthieux & Meurs, 2015; Boll et al., 2017). Additionally, higher rates of part-time employment among women further curtail cumulative work experience, exacerbating human capital deficits and widening earnings gaps (Blau & Kahn, 2007; Mincer & Polachek, 1974). Critics of the human capital framework argue that qualifications and experience alone cannot fully account for gendered pay inequities, citing systemic discrimination and occupational segregation as overlooked factors (Grybaitė, 2006; Lips, 2013). Nonetheless, empirical studies affirm that human capital determinants remain statistically significant in explaining earnings disparities (e.g., Boll et al., 2017).

Globally, women earned an average of 14.1% less than men in 2023, marking a reduction from the 17.5% gap recorded in 2022 (WEF, 2023). Across OECD nations, the GPG in hourly wages narrowed from 19% in 1996 to 12.5% in 2019, translating to women earning 87.5 cents for every euro (or dollar) earned by men in comparable roles (OECD, 2021). Despite this progress, disparities persist; in East and Southern Africa, women earn 21% less than men (UN Women, 2023), while Kenya has an unadjusted hourly GPG of 17.7% and a monthly gap of 31.3%. The latter disparity reflects women's reduced working hours in wage employment, driven by disproportionate unpaid care responsibilities, labor market discrimination, and individual constraints (UN Women, 2023).

Studies on the gender pay gap seeks to disentangle the extent to which earnings disparities stem from employer discrimination versus differences in productivity-related observable characteristics. A common methodological approach decomposes the GPG into two components: (1) the *"explained"* portion, attributable to observable productivity-related factors (e.g., education, experience), and (2) the *"unexplained"* residual, which serves as a proxy for potential discrimination (Firpo et al., 2009, 2018). The share of the gap linked to pre-labor market skills and occupational segregation varies cross-nationally, with more granular analyses typically attributing a larger proportion to these measurable factors. However, even after controlling for skills, occupation, experience, and tenure—variables potentially shaped by systemic bias—at least one-third of the GPG persists in most studies. This residual disparity suggests entrenched inequities unrelated to productivity. Notably, even when occupational sorting is assumed to be nondiscriminatory, significant pay gaps endure within specific industries and roles, underscoring persistent intra-occupational inequities (Black et al., 2008).

Empirical literature on Sub-Saharan Africa, especially Kenya, consistently documents higher wages for men compared to women, yet scholars remain divided on whether this disparity stems predominantly from *explained* or *unexplained* factors (Agesa et al., 2013; Abdiaziz & Kiiru, 2021; Omanyo, 2021). Most SSA studies, including those in Kenya, have centered on the conditional mean gender pay gap, which evaluates unequal pay for equal work across the whole labor market (e.g., Kim, 2020). However, critical gaps persist in analyzing the unconditional earnings distribution (i.e., disparities across all income levels) and sector-specific earnings inequities within Kenya. Existing insights into Kenya's public-private sector pay gap rely heavily on Omanyo's (2021) 2015/2016 data and Agesa et al.'s (2009) 2005/2006 data findings for the whole labor market, both of which highlight earnings disparities but leave causal mechanisms underexplored. Methodological limitations further constrain current research. Key studies in Kenya (e.g., Kabubo-Mariara, 2003; Agesa et al., 2013; Abdiaziz & Kiiru, 2021) often overlook occupational segregation—the systemic clustering of women into lower-paying roles—by treating occupational choices and structures as exogenous rather than endogenous. And these analyses neglect nuanced dimensions of the gender pay gap, such as disparities among workers of varying education levels or across generational cohorts, limiting understanding of how inequities manifest demographically.

Theoretical frameworks posit that gender pay gaps between public and private sectors arise from divergent wage-setting mechanisms: public-sector wages are shaped by political and bureaucratic processes, whereas private-sector compensation aligns with market-driven forces (Campos et al., 2017; Dickson et al., 2014; Chassamboulli & Gomes, 2023). Public-sector employment often yields more equitable wage structures for women due to standardized pay scales, stronger union representation, and rigorous enforcement of anti-discrimination policies (Pfeifer, 2008; Antonczyk et al., 2010; Card et al., 2020). Conversely, occupational segregation—the unequal distribution of men and women across industries and roles—remains a key driver of aggregate earnings disparities, as female-dominated sectors tend to offer lower wages (Orraca et al., 2016; Ismail et al., 2017; Goy & Johnes, 2012; Demoussis et al., 2010; Khitarishvili et al., 2018). Educational attainment and age (a proxy for work experience) further mediate these gaps. Workers with varying education levels and career tenures drift toward distinct occupations, amplifying disparities.

1.2 Thesis Actuality and Justification

Kenya's labor market is characterized by persistent gender disparities in earnings and occupational distribution, despite progressive legal and institutional reforms. The 2010 Constitution and subsequent labor laws, such as the Employment Act of 2007, explicitly prohibit gender discrimination and promote equitable labor practices. However, structural inequities rooted in socio-cultural norms, institutional inertia, and labor market segmentation continue to hinder gender parity. Women constitute 49.7% of Kenya's labor force but face systemic barriers, including occupational segregation, wage gaps, and disproportionate unpaid care responsibilities (Kenya Labor Market Profile [KLMP], 2024; UN Women, 2024).

Kenya's dualistic labor market structure—comprising a regulated formal sector (15.9% of total employment) and a huge informal sector (84.1% of total employment)—exhibits divergent wage-setting mechanisms. The formal sector employs structured frameworks such as collective bargaining agreements [CBAs] and statutory minimum wages, while the informal sector remains unregulated, relying on market-driven negotiations. Notably, CBAs cover only 24% of formal wage employees (3.7% of total employment), with stark sectoral disparities: education and public administration account for 44% of covered workers, compared to 3.5% in manufacturing (KNBS *Economic Survey*, 2023). This imbalance reflects institutional gaps in enforcing labor rights, particularly in male-dominated industries like manufacturing, where unionization is fragmented.

The public sector, governed by administrative pay grades and the Salaries and Remuneration Commission [SRC], has marginally better gender parity in managerial roles (49.6% women in senior/middle management). However, overlapping mandates between the SRC and county governments create jurisdictional conflicts, undermining cohesive wage determination (KIPPRA, 2018). Conversely, the private formal sector ties wages to productivity and market dynamics, which often disadvantage women due to occupational clustering in low-productivity roles (e.g., 66.2% of women in household employment). These sectoral dynamics justify the thesis's focus on comparing GPG trends across sectors (formal and informal), as structural inequities in wage governance and enforcement mechanisms likely exacerbate disparities in the informal sector.

Kenya's pronounced youth bulge—with individuals aged 15–34 constituting 35% of the population and 80% under 35—presents both opportunities and challenges for equitable labor market outcomes. The country's demographic transition, marked by a declining age dependency ratio (69% in 2022), signals potential for a demographic dividend, yet systemic barriers persist, particularly for young women. Annual labor market entries exceed 800,000 youth, but only 15% secure stable employment, with most relegated to informal, low-wage roles lacking social protection. This structural mismatch is compounded by a 20% NEET rate (24% for women vs. 15% for men), reflecting gendered disparities exacerbated by caregiving responsibilities and cultural norms. Analyzing GPG across age cohorts is critical to unravelling how human capital elements—such as education, vocational training, and sectoral participation—differentially influence earnings over the life course. Younger cohorts, despite policy-driven gains in educational access, face overqualification in informal sectors and discrimination in male-dominated industries, while older workers contend with entrenched occupational segregation and motherhood penalties. By disaggregating GPG by age, this thesis identifies cohort-specific drivers of inequality, enabling targeted interventions to align Kenya's youth-centric policies with the balanced needs of its dynamic workforce.

Human capital disparities are central to Kenya's GPG. While women's educational attainment has improved—with female net enrollment rates surpassing males at secondary levels—returns to education remain gendered. Highly educated women are still underrepresented in high-productivity sectors (e.g., 17.2% in electricity/gas jobs) despite constituting 50% of managerial positions (KLMP, 2024; World Bank, 2025). Conversely, low-educated women are trapped in informal, low-wage roles (86% informal employment rate for women vs. 77% for men). The NEET rate further highlights systemic failures: 24% of women aged 15–24 are neither employed nor in training, compared to 15% of men (KLMP, 2024). This bifurcation aligns with the thesis focus, positing that educational stratification perpetuates hierarchical pay gaps.

Occupational segregation is a critical driver of Kenya's GPG. Women are overrepresented in care-oriented sectors (e.g., 53.4% in health/social work) and underrepresented in high-productivity industries like extractives (12.8%) and manufacturing (22.9%). Vertical segregation compounds this: women dominate lower-tier roles (e.g., domestic work, retail) while men occupy technical and leadership positions. This clustering reflects societal norms that devalue "feminized" roles and restrict women's mobility. For example, 68.3% of working women are in vulnerable employment, compared to 51.8% of men (KNBS *Economic Survey*, 2023). These patterns validate the thesis hypothesis that occupational sorting—shaped by systemic biases—accounts for significant earnings differentials.

The multi-theoretical framework of the thesis—integrating human capital, labor market segmentation, and discrimination theories—resonates with Kenya's labor market realities. The human capital model is contextualized by disparities in returns to education: while women's tertiary enrollment has risen, their wages lag due to occupational hierarchies and societal expectations. Labor market segmentation theory explains why informal sector workers (disproportionately women) lack social protection, perpetuating precarity. Discrimination theory elucidates institutional biases, such as weak enforcement of anti-discrimination laws and cultural norms relegating women to unpaid care work. Kenya's policy landscape further justifies this analysis. The 2023 National Wage Policy draft seeks to bridge GPGs but remains unimplemented, while devolution has created fragmented wage structures. Addressing these gaps requires empirical insights into sectoral disparities, educational stratification, and occupational segregation—precisely the focus of this thesis.

Thus, the interplay of Kenya's labor market structures, socio-cultural dynamics, and institutional frameworks creates a complex landscape where gender pay gaps persist despite legal advancements. This thesis contributes to the expanding discourse on gender pay gaps by engaging with contemporary research on labor market inequalities in SSA, including seminal works by scholars such as Nordman et al. (2016), Kim (2020), and Danquah et al. (2021). Focusing on Kenya, I seek to illuminate the structural and institutional mechanisms underlying gender pay gaps by analyzing disparities across Kenya's formal (public and private) and informal sectors, as well as within distinct age cohorts. I further evaluates how educational attainment influences these inequities and examines the role of occupational and industrial segregation in perpetuating gendered earnings differentials. While building on foundational studies in Kenya by Agesa et al. (2009, 2013), Abdiaziz and Kiiru (2021), and Omanyo (2021), this study addresses critical gaps in

Kenya's empirical literature, which often overlooks the interplay of sectoral dynamics, demographic heterogeneity, and systemic segregation.

To advance this inquiry, the thesis applies the 2021 Kenya Continuous Household Survey [KCHS-2021], employing a multi-method decomposition analytical framework that integrates the standard Oaxaca-Blinder decomposition (Oaxaca, 1973; Blinder, 1973) to disentangle explained and unexplained gender pay gaps at mean level, the Machado-Mata decomposition (Machado & Mata, 2005) to map disparities across the earnings distribution by education level, and the Reweighting RIF-Oaxaca decomposition (Firpo et al., 2009, 2018) to decompose the GPG across Kenya's formal (public and private) and informal sectors and across age cohorts, and the Brown-Moon-Zoloth [BMZ] decomposition to account for occupational shares and distributional in explaining the GPG. By combining these approaches and interrogating sectoral disparities, educational stratification, and occupational segregation, the results of this thesis not only provide critical insights into the structural drivers of inequities but also uncover the subtle mechanisms—such as discriminatory wage-setting practices, occupational clustering, and uneven returns to education—that sustain inequities.

1.2 Objectives of the study

This thesis comprises three interrelated empirical studies designed to explore the gender pay gap in Kenya through an integrative analytical framework. The first empirical study investigates sectoral and generational disparities by comparing GPG trends in Kenya's formal (public and private) and informal sectors and across age cohorts. The second explores the role of educational attainment in moderating earnings inequalities, examining whether education stratification yield divergent pay gap patterns between highly educated and low-educated workers. The third evaluates how occupational and industrial segregation—the systemic clustering of women into lower-paying roles and sectors—shapes gendered earnings differentials.

To this end, the thesis has three specific objectives:

i. To examine the sources and magnitude of the gender pay gaps in Kenya's formal (public and private) and informal sectors and across different age cohorts.
ii. To assess whether highly educated women confront a significant *glass ceiling* effect, while low-educated women experience a *sticky floor* effect.

iii. To evaluate the role of occupational and industrial segregation in driving gender pay differentials in Kenya.

In line with these specific objectives, the thesis seeks to address the following leading research questions:

1) Is the public sector more financially rewarding? Is gender pay discrimination distinct across age cohorts and between formal and informal sectors, given that sectoral choice is typically a predetermined endogenous process?
2) How does the GPG manifest itself across the earnings distribution for low-educated and highly educated workers? To what extent do disparities in observable characteristics versus discriminatory returns to these traits drive the GPG by education stratification?
3) What is the extent of divergence in occupational, industrial, and sectoral structures between men and women in Kenya? To what extent do gender differences in occupational and industrial structures contribute to the earnings disadvantage faced by women?

1.3 Thesis Hypotheses

Accordingly, I formulated the following hypotheses:

1. $\boldsymbol{H_1}$: The gender pay gap can primarily be explained by the human capital elements, with significant varying effects across employment sectors and age cohorts.
2. $\boldsymbol{H_2}$: Highly educated women confront a significant glass ceiling effect, while low-educated women experience a sticky floor effect.
3. $\boldsymbol{H_3}$: Occupational status and structures of men and women significantly accounts for the gender pay gap.

1.4 Thesis Structure and Organization

The thesis is structured as follows: **Chapter 2** contextualizes Kenya's labor market within its historical evolution, legal frameworks, and institutional structures. It examines the development of gender equality initiatives, labor policies, sectoral dynamics, wage-setting mechanisms, and social dialogue processes, emphasizing their interplay with systemic inequities

Chapter 3 delineates the theoretical framework underpinning the gender pay gap, combining perspectives from the human capital model, labor market segmentation and discrimination theories, and feminist/gender scholarship. **Chapter 4** examines methodological approaches to decomposing GPG, beginning with the foundational Oaxaca-Blinder [O-B] decomposition grounded in the Mincer earnings function. It further addresses methodologies to address selectivity bias, including the Heckman two-step correction model and the BFG approach (Bourguignon et al., 2007), which collectively inform the empirical strategies deployed in subsequent analyses. **Chapter 5** contextualizes the study's empirical scope by detailing the dataset, variable construction, and analytical procedures, while presenting key descriptive statistics to frame the findings of the sectoral, educational, and segregation-focused investigations.

Chapter 6 addresses the first research objective by analyzing the GPG across Kenya's formal (public and private) and informal sectors and within distinct age cohorts: youth (15–34 years) and older workers (35–65 years). This empirical chapter estimates earnings determinants and quantifies GPG at the conditional mean and across the unconditional earnings distribution. The analysis employs a dual decomposition framework: the standard Oaxaca-Blinder method isolates explained (compositional) and unexplained (structural) components of the GPG at mean level, while the reweighted RIF-Oaxaca decomposition (Firpo et al., 2009, 2018) extends this analysis to examine distributional shifts, such as disparities at higher or lower earnings percentiles.

Chapter 7 advances the thesis's second objective by systematically examining how educational attainments shape Kenya's gender pay gap. To the best of existing scholarly works, no prior study in Kenya has decomposed the GPG across educational strata. Addressing this gap, the analysis employs quantile regression to estimate how covariates influence earnings across the earnings distribution, coupled with the Machado-Mata decomposition method (Machado & Mata, 2005). This dual approach disentangles observed and counterfactual GPG at various deciles, partitioning disparities into two components: (1) differences in observable characteristics and (2) differential returns to those endowments between highly educated and low-educated workers.

Chapter 8 advances the third thesis objective by investigating the role of occupational and industrial segregation in Kenya's gender pay gap. The analysis begins by constructing a dissimilarity index to quantify disparities in occupational and sectoral distribution between men and women. Recognizing occupational choice as an endogenous process shaped by systemic factors, the chapter models occupational selection using observable characteristics to simulate a counterfactual scenario where female workers face the same structural determinants as their male counterparts. This counterfactual framework isolates how gendered occupational sorting—rather than individual preferences—perpetuates earnings inequities. Afterwards, the chapter employs the BMZ decomposition technique to disentangle *intra-occupational* disparities from *inter-occupational* disparities.

Chapter 9 brings together the thesis's empirical findings into a cohesive narrative, highlighting cross-cutting themes such as the persistent influence of occupational segregation, gender pay gap by education stratification, and the sectoral dynamics of wage disparities. It concludes with actionable policy recommendations—to advance gender equity in Kenya's labor market and it also outlines directions for future research.

2. GENDER AND KENYA'S LABOR MARKET: STRUCTURAL DYNAMICS, POLICY FRAMEWORKS, AND INSTITUTIONAL REFORMS

This chapter places Kenya's labor market dynamics within historical, legal, and institutional contexts, tracing the evolution of labor policies, labor market structures, wage-setting mechanisms, and social dialogue frameworks. Through this integrative approach, it lays the groundwork for empirical investigations into how systemic inequities—rooted in educational stratification, sectoral divides, and cultural norms—perpetuate gendered economic exclusion, aligning with the thesis's objectives to unravel and address these persistent challenges.

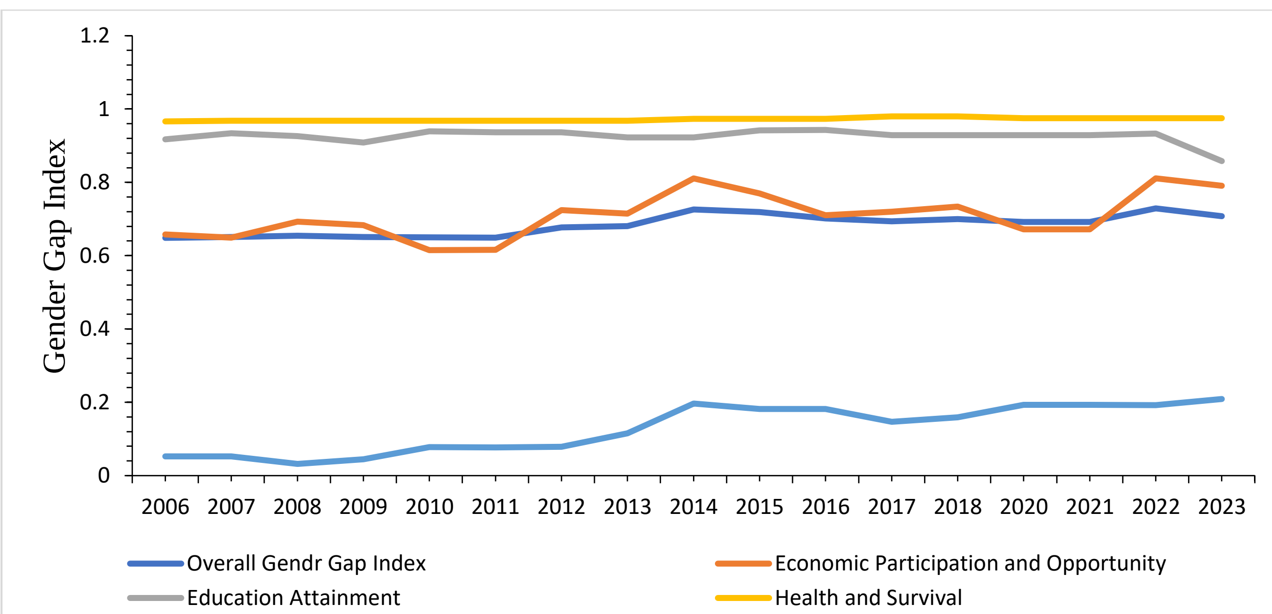
2.1 Kenyan Context: Gender inequality

Kenya's commitment to gender equality, which gained momentum in the early 1990s, has yielded significant strides in dismantling systemic barriers for women. Historically excluded from full labor market participation due to entrenched societal discrimination, women have increasingly benefited from legal reforms enacted since 2002. These efforts culminated in the 2010 Constitution of Kenya, a transformative document that codifies women's rights as inalienable human rights, guaranteeing dignity and equitable access to economic, social, political, and cultural opportunities (Republic of Kenya, 2010). Complementing this constitutional framework, the Employment Act of 2007 explicitly prohibits workplace discrimination, while the Employment and Labor Relations Court Act and Labor Institutions Act institutionalize gender-neutral labor practices, fostering equitable dispute resolution and workplace governance (Republic of Kenya, 2010).

Kenya has exhibited robust political commitment to advancing gender equality, aligning with central, regional, and international conventions and protocols. The nation's legal framework supporting working women's rights scored 84 out of 100 in 2024, surpassing the SSA regional average of 74, though it underperforms in areas such as parenthood support, entrepreneurship incentives, pension equity, and asset rights (World Bank Group, 2024). Institutional mechanisms like the National Gender and Equality Commission, established under the 2011 National Gender and Equality Commission Act, are tasked with eliminating discrimination and fostering equitable opportunities (KLMP, 2024). Despite these efforts, entrenched cultural norms surrounding gender roles and female empowerment perpetuate systemic inequities. Women's economic participation remains constrained by disproportionate burdens of unpaid caregiving and domestic labor, which restrict their mobility, access to market resources, and engagement in productive activities (USAID, 2024). These challenges are reflected in Kenya's Gender Inequality Index ranking of 139 out of 162 countries, underscoring persistent disparities in health, education, and labor market outcomes. Kenyan women face barriers in accessing non-traditional sectors, experience slower career advancement, and endure higher dismissal rates compared to men. Notably, Kenya's ongoing devolution process presents novel opportunities to enhance women's political representation at the county level, signaling potential pathways to address structural inequities through localized governance reforms (KLMP, 2024).

Kenya's gender equality initiatives have achieved marked progress, as evidenced by its 77th global ranking in the 2023 Global Gender Gap Index (WEF, 2023). The country has closed 71% of its gender disparity, surpassing both the SSA average (68.2%) and the global benchmark (68.4%). Notable advancements include an economic empowerment and opportunity index of 0.791 in 2023 and an educational attainment index of 0.933 in 2022 (see *Figure* 1), reflecting strides in women's workforce integration and educational access. These metrics underscore the efficacy of Kenya's policy frameworks in advancing gender equity and fostering inclusive development.

Figure 1: Kenya's Gender Gap Overtime, 2000-2023



Source: Author's construction based on Global Gender Gap Reports (2006-2023).

2.2 Evolution of Kenya's Labor Policies and Reforms

Kenya's labor market policies have undergone significant transformations since independence, shaped by shifting economic priorities, globalization, and socio-political imperatives. This evolution can be categorized into three distinct phases: the post-independence *Kenyanization* era, the adoption of *Active Labor Market Policies [ALMPs]*, and the neoliberal macroeconomic reforms of the late 20th century. Each phase reflects the interplay between state intervention, market forces, and institutional adaptations, with varying effects on formal and informal employment, social dialogue, and workers' rights.

Post-independence, Kenya's government prioritized *Kenyanization*—replacing non-citizen workers in public and private sectors with Kenyan nationals. This policy attempted to decolonize the labor market and empower Africans. By 1971, African representation in the public service surged from 14.6% (1964) to 97%, while the private sector achieved 95% Kenyanization by 1981 (ILO, 1995; Republic of Kenya, 1983). However, the policy focused on *job realignment* rather than *job creation and gender balance*. Wage employment grew modestly at 2.8% annually (1964–1972), with the government acting as the "employer of last resort" (Omolo, 2002). Tripartite agreements (1964, 1970, 1979)—intended to compel employers to expand payrolls by 10%—failed due to non-compliance; employers instead converted casual workers to permanent roles without increasing overall employment (Institute of Economic Affairs, 2010).

Subsequently, in the 1970s, Kenya shifted toward ALMPs following ILO recommendations to address skills mismatches and unemployment (Institute of Economic Affairs, 2010). The 1972 ILO mission recognized the *Jua Kali* (Swahili for "hot sun") sector—a term for informal, small-scale enterprises—as a critical driver of employment. Informal employment, defined as non-wage work characterized by labor market insecurity and weak regulation, grew rapidly at 8.4% annually (1975–1985), outpacing formal sector growth (3.6%) (Republic of Kenya *Various Economic Survey*). By 1985, informal employment accounted for 0.288 million jobs, up from 0.131 million in 1975. The government established the National Employment Bureau [NEB] in 1986 to improve labor market information and job placement. However, the NEB struggled with enforcement due to inadequate legal backing and resource constraints—Employment Act of 2007. Private employment agencies emerged in urban centers, but rural areas remained underserved, exacerbating regional disparities (Republic of Kenya, 1983).

The 1980s–1990s saw Kenya adopt Structural Adjustment Programs and liberalization policies, which prioritized fiscal discipline, privatization, and export-led growth. These reforms triggered formal sector job losses, accelerating informalization. By 2008, informal employment constituted 80.5% of total employment, up from 20.6% in 1986. The *Jua Kali* sector absorbed displaced workers but offered precarious conditions: low wages, no social protection, and minimal unionization. Post-2000 reforms, including the Employment Act of 2007 and Labor Institutions Act of 2007**,** sought to modernize labor laws by codifying rights to collective bargaining and establishing dispute resolution mechanisms. However, enforcement gaps persisted, particularly in rural counties.

Gender inclusivity in labor policies remains limited. The Central Organization of Trade Unions [COTU] reserves two Executive Board seats for women and youth, yet only five of 24 members are women (COTU-Kenya, 2023). The 2010 Constitution's recognition of collective bargaining indirectly supports gender equity, but no explicit anti-discrimination laws are highlighted. The draft National Wage Policy (2023) seeks to bridge gender pay gaps by aligning minimum wages with living wages, though its approval is pending (Ministry of Labor and Social [MLSP] Protection, 2023). Effectiveness is mixed: while formal sector representation improved, informal sector workers (disproportionately women) lack protections.

Furthermore, Kenya's labor market institutions exhibit pronounced heterogeneity in policy implementation across counties, especially along urban-rural divides. The National Employment Bureau and private employment agencies remain concentrated in urban centers, marginalizing rural regions in access to formal employment services (Institute of Economic Affairs, 2010). Judicial inequities further compound this gap, as the Employment and Labor Relations Court operates in only 13 of Kenya's 47 counties, restricting rural populations' access to labor justice. Post-devolution, county-level consultative committees have struggled to harmonize wage structures, particularly in critical sectors like health and education, due to fragmented coordination between national and subnational authorities (COTU-Kenya, 2023). Sectoral imbalances in CBA coverage underscore institutional disengagement, with education achieving 44% coverage compared to a mere 3.5% in manufacturing—a disparity reflecting uneven unionization and advocacy efforts (Kenya National Bureau of Statistics, 2023).

Economic shocks heavily influence Kenya's labor markets. SAPs and 1990s liberalization triggered formal sector job losses, pushing workers into informal sectors. During the 2008 global crisis and COVID-19 pandemic, formal employment contracted, while informal sector resilience cushioned the effects (Ministry of Labor and Social Protection, 2023). Real GDP growth fluctuations (averaging 3.52%, 1986–2008) correlate with informal employment spikes. Business cycles also affect wage dynamics: CBAs in sectors like construction saw real wage declines during downturns (2022–2023), while education and mining secured increases (KNBS, 2023). In all in all, Kenya's labor policies have transitioned from state-led job realignment to market-driven reforms, with mixed outcomes. Gender inclusivity and county-level implementation remain weak, while business cycles exacerbate informalization. Sustained institutional capacity-building and targeted gender reforms are critical for equitable labor market outcomes.

2.3 Labor Market Social Partners

Social partners play a critical role in advancing core labor rights and social justice by safeguarding workers' freedom of association and collective bargaining. These key stakeholders are institutionally represented through three primary entities: the government, trade unions, and employers' organizations. The Kenyan government stands as the foremost employer within the formal sector, responsible for approximately 25% of total formal employment. Central to labor market governance is the Ministry of Labor and Social Protection, which operates through five specialized departments (MLSP, 2022).

Trade unionism in Kenya emerged in the early 1930s and has since evolved within a legal framework that safeguards workers' rights. Contemporary legislation guarantees employees, including those in Export Processing Zones [EPZs], the freedom to form or join unions, engage in collective bargaining, and seek reinstatement if dismissed for union activities. Anti-union discrimination is explicitly prohibited, and public sector workers retain the right to unionize without restriction (KLMP, 2024). However, unionization efforts have faced systemic challenges, including the decades-long contraction of Kenya's formal sector, weak enforcement of labor laws, and institutional inefficiencies such as protracted dispute resolution processes, outsourcing practices, and mass retrenchments.

In response to these obstacles, the COTU-Kenya, Kenya's foremost trade union federation, has pivoted its strategy toward organizing informal economy workers. Since 2016, COTU-Kenya has expanded its influence by affiliating seven new unions, including the re-affiliated Kenya National Union of Teachers, bringing its total affiliates to 47. This revitalization has spurred significant membership growth: data from COTU-Kenya revealed a 22% surge in unionized workers between 2016 and 2023, culminating in approximately 3.1 million members by 2023 (COTU–Kenya, 2023). These gains underscore COTU-Kenya's adaptive approach to counteracting formal sector decline while advocating broader labor rights in Kenya's increasingly informalized economy.

Kenya's trade union density—the proportion of unionized workers relative to formal employment—stood at 16% in 2023, a figure that notably exceeds rates observed in neighboring East African countries (KLMP, 2024). Trade unions in Kenya are predominantly sector-based, with key representation in agriculture and plantations, county government, commercial and food industries, and education. A minority of general unions operate across multiple sectors. While agricultural workers globally tend to be less organized, Kenya's large plantation workers form a significant exception, constituting 17% of total union membership due to their concentrated worksites (KLMP, 2024).

The Federation of Kenya Employers [FKE], established in 1959, represents the final pillar of Kenya's tripartite social dialogue framework. Functioning independently of government and political affiliations, the FKE serves as the primary advocate for employer interests across both public and private sectors. Its membership excludes civil service and security forces but encompasses over 4,000 businesses directly and indirectly through 15 sector-specific associations, spanning industries from agriculture to technology. This diverse membership base includes enterprises of all sizes, from small enterprises to large corporations, reflecting Kenya's heterogeneous economic landscape. The FKE actively engages in shaping labor policy through its participation in national and international tripartite institutions, where it collaborates with trade unions and government bodies to negotiate labor standards, wage policies, and dispute resolution mechanisms (KLMP, 2024).

2.4 Labor Market Social Dialogue

Kenya's 2010 Constitution marked a pivotal advancement in labor rights by formally recognizing the right to collective bargaining, positioning the country among the few with such constitutional safeguards. Unlike frameworks that impose a broad duty to negotiate in good faith

(ILO, 2022), Kenya's legal regime mandates *specific obligations* for employers and unions, delineating clear procedural requirements for bargaining processes (KIPPRA, 2018). This constitutional commitment is further reinforced by Kenya's ratification of core international labor conventions, aligning its domestic policies with global standards.

In recent years, social partners—trade unions, employers' organizations, and the government—have deepened bipartite negotiations to institutionalize CBAs, which are legally binding contracts outlining terms of employment between unions and employers (or employer groups). These agreements are negotiated either at the enterprise level (e.g., individual companies) or sectoral level (e.g., entire industries). A prominent example is the Kenya County Government Workers Union, a COTU affiliate representing public sector employees. To initiate negotiations, the union must first secure a *Recognition Agreement* from one of Kenya's 47 county governments. Once recognized, it negotiates and formalizes CBAs on behalf of county workers, addressing wages, working conditions, and dispute resolution mechanisms. This structured approach has enabled gradual progress in labor relations, though challenges persist. For instance, while CBAs in sectors like education and public administration cover significant worker cohorts (KLMP, 2024), others, such as agriculture, lag due to fragmented unionization. The constitutional emphasis on specificity over generality in bargaining obligations ensures accountability but also demands robust institutional capacity—a test for Kenya's evolving labor landscape.

As depicted in Figure 2, the trajectory of CBAs in Kenya reflects both volatility and resilience in labor relations since 2010. The decade began with deteriorating industrial relations, culminating in widespread unrest and sectoral strikes triggered by eroding employment terms and faltering CBA implementation. By 2020, the number of unionized workers covered by CBAs plummeted to a historic low, exacerbated by the government's suspension of large-scale agreements under pandemic lockdown measures. However, post-2020 recovery efforts spurred a dramatic rebound: from 2022 to 2023 alone, CBA coverage surged by 69%, culminating in a peak of approximately 743,000 protected workers—the highest recorded since 2010 (KLMP, 2024). This resurgence underscores the critical role of institutional adaptability in revitalizing labor rights amid systemic shocks.

Figure 2: Number of CBAs and Unionized Employee's Coverage in Kenya, 2010-2023

Source: KLMP (2024) based on Kenya National Bureau of Statistics, Economic Surveys

In 2023, the CBAs covered 24% of union-eligible wage employees in Kenya, though this represented just 3.7% of total employment—a reflection of the economy's large informal sector (KNBS *Economic Survey*, 2024). Sectoral disparities in CBA implementation were stark. The manufacturing sector, despite leading with 133 CBAs, accounted for only 3.5% of covered unionized workers, underscoring fragmented unionization within the industry. In contrast, the education sector's 48 CBAs protected 44% of all CBA-covered workers, highlighting its centralized workforce and strong union presence. Similarly, three CBAs in public administration, defense, and social security sectors covered an additional 44% of unionized employees, demonstrating concentrated bargaining power in public institutions. While CBAs offer critical safeguards in structured sectors, their limited reach in informal and fragmented industries perpetuates vulnerabilities. Strengthening sector-specific bargaining frameworks and expanding coverage remain vital to equitable labor protection.

2.5 Wage-Setting Mechanisms

Kenya's labor market is characterized by a dualistic wage-setting framework, where formal and informal sectors operate under divergent regulatory and socio-economic conditions. The formal sector employs structured mechanisms such as statutory minimum wages and CBAs, while the informal sector remains predominantly unregulated, fostering exploitative wage practices.

2.5.1 Formal sector wage-settings

Kenya's formal sector wage determination system operates through a structured framework governed by statutory regulations, collective bargaining, and tripartite institutions. The Labor Institutions Act of 2007 and Employment Act of 2007 provide the legal foundation, mandating minimum wage standards and formalizing dispute resolution mechanisms. Central to this system are Wages Councils, which facilitate sector-specific minimum wage negotiations through tripartite consultations among government, employers, and unions. While Kenya initially established 17 sector-specific councils, only the General Services and Agriculture Councils remain active, substantially narrowing their sectoral reach (KLMP, 2024).

Another critical mechanism is CBAs, negotiated at the enterprise or sectoral level, often led by unions such as the Kenya County Government Workers Union (a COTU affiliate). By 2023, CBAs covered 24% of formal wage employees, though disparities persist: education and public administration sectors accounted for 44% of covered workers, compared to a mere 3.5% in manufacturing (KNBS, 2023). Post-pandemic recovery spurred a 69% surge in CBA coverage between 2022 and 2023, extending protection to 743,000 workers. However, inflationary pressures eroded real wages in the agriculture and construction sectors despite this expansion (KLMP, 2024).

The Ministry of Labor and Social Protection periodically revises nominal minimum wages, with the latest adjustment in 2022 raising rates by an average of 11% (KLMP, 2024). These adjustments highlight stark spatial inequities: urban minimum wages (e.g., Nairobi at KSh 23,868/month) remain nearly double rural rates (e.g., KSh 10,107/month in agriculture), as reported in the KNBS *Economic Survey* (2023). Tripartite institutions further shape wage governance. The National Labor Board advises the MLSP on policy formulation, while the Salaries and Remuneration Commission oversees public sector compensation. However, overlapping mandates and ambiguities in the SRC's role have generated conflicts, especially in county-level health sector wage determinations (KIPPRA, 2018).

2.5.2 Informal Sector Wage-Setting Dynamics

Kenya's informal sector operates largely outside the purview of formal wage regulations. Wage determination in this sector relies on informal negotiations, market-driven forces, and unregulated dynamics influenced by customary practices. A critical challenge is the absence of legal protections: informal workers, such as gig economy participants and *Jua Kali* artisans, are excluded from statutory minimum wage guarantees and CBAs. By 2024, CBAs covered only 3.7% of total employment, leaving the vast majority of informal workers exposed to exploitative wage practices (KLMP, 2024).

The gig economy presents additional challenges, particularly for platform workers such as ride-hailing drivers, who face algorithmic wage-setting mechanisms and income instability. Domestic platform workers, for instance, are especially marginalized: only 1% are unionized, and most earn below the statutory minimum wage (KLMP, 2024). Their exclusion from formal contracts denies them labor protections under the Labor Relations Act of 2007, perpetuating precarity. These systemic gaps highlight the informal sector's reliance on fragmented, inequitable wage-setting practices, underscoring the need for policy interventions to address regulatory exclusion and social inequities.

2.6 The Kenyan Labor Market Structure

Kenya's labor market exhibits a dual structure, comprising a regulated formal sector and a predominantly unregulated informal sector. Employment trends indicate that the informal sector serves as the primary driver of job creation, absorbing the majority of the workforce. However, informal employment is characterized by systemic precarity, marked by insecure tenure, inadequate wages, minimal social protections, and substandard occupational safety conditions. These vulnerabilities starkly contrast with the formal sector's structured employment frameworks, which offer greater stability and regulatory safeguards. The informal economy predominantly consists of small-scale, low-technology enterprises with minimal capital and labor inputs. Its accessibility—due to low barriers to entry and reliance on rudimentary tools—enables widespread participation but perpetuates low productivity.

The KNBS *Economic Survey* (2023) highlights persistent gender and structural disparities in Kenya's labor market. In 2023, women's labor force participation rate stood at 72.2%, slightly below men's 75.3%, with women comprising 49.7% of the total labor force. Despite steady employment growth across formal and informal sectors since 2014, significant gaps persist: women accounted for only 39% of total employment in 2021, with an employment rate of 60.3% compared to men's 70.4%. Total wage employment outside small-scale agriculture and pastoralism rose from 18.3 million in 2021 to 19.1 million in 2022, reflecting a 65.3% employment-to-population ratio for individuals aged 15–65. The informal sector remains the dominant employer, growing by 4.6% to 16.0 million jobs (84.1% of total employment), while the formal sector expanded marginally to 3.2 million jobs (15.9% of total employment), including 0.9% self-employed workers. Sectorally, 68% of formal jobs are concentrated in the private sector, with the public sector contributing 32% (KNBS *Economic Survey*, 2023).

Kenya's labor market exhibits persistent gender disparities, despite incremental progress in female representation across certain sectors. Women constitute 46.2% of formal wage employment and 53.8% of informal wage employment, compared to men's 47.1% and 52.9%, respectively (KNBS *Economic Survey*, 2023). However, women remain disproportionately concentrated in vulnerable employment—characterized by informal arrangements, limited social protection, and heightened exposure to economic shocks. In 2022, 68.3% of working women were in vulnerable roles, significantly higher than men's 51.8%.

Gendered occupational segregation further entrenches inequalities. Women dominate household employment (66.2%) and health/social work (53.4%), sectors typically marked by lower wages and precarious conditions. Conversely, they are underrepresented in high-productivity industries but slightly overrepresented in professional and technical roles (e.g., senior/middle management, where they held 49.6% of positions in 2019, ranking Kenya among global leaders in gender parity for such roles (World Bank *Gender Data Portal*, 2025). Nevertheless, this progress is tempered by vertical segregation, as women remain clustered in lower-tier service, sales, and elementary occupations (KNBS *Economic Survey*, 2023). This stratification perpetuates the gender pay gap, underscoring systemic barriers to equitable economic participation

Table 1 lists pronounced gender disparities in Kenya's labor market, with women experiencing significantly higher unemployment rates and lower formal employment participation compared to men. These inequities are closely linked to the disproportionate burden of domestic and caregiving responsibilities borne by women, which often channels them into part-time or informal work within low-productivity sectors. Curiously, however, Kenyan women exhibit a marginally higher employer rate than men, suggesting subtle variations in economic participation across employment categories.

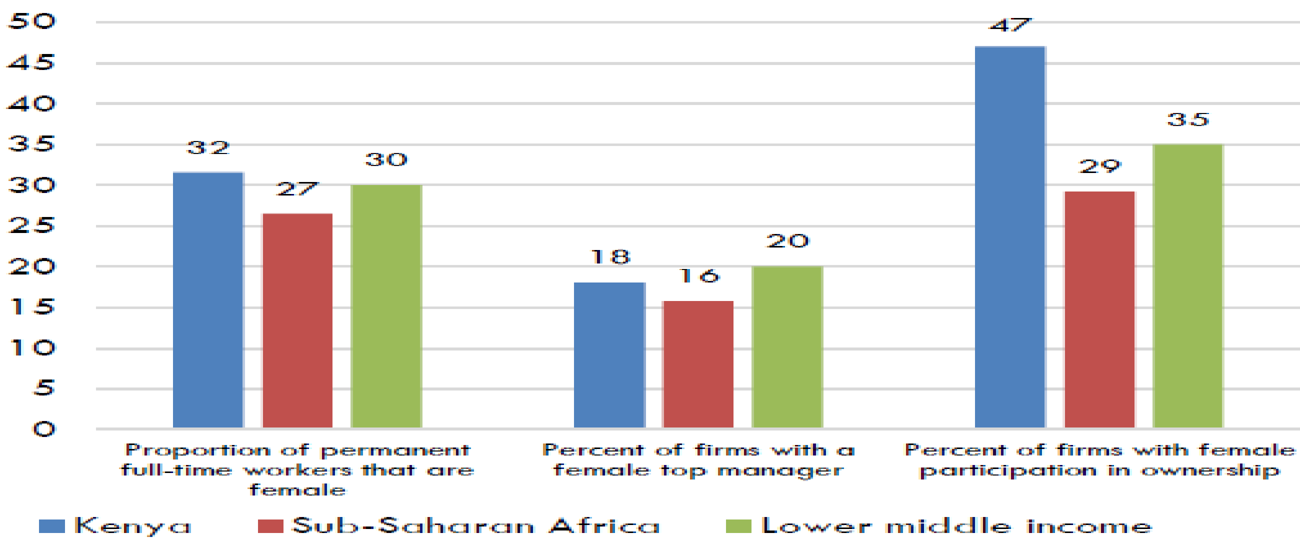
Table 1: Gender Gaps by Employment in Kenya, 2021

	Men	Women
Participation rate	73%	63%
Employment share	52%	48%
Unemployment rate	3.9%	7.6%
Employees share	65%	35%
Employers share	1.4%	1.7%
Informal employment rate	77%	86%

Source: Kenya Labor Market Profile (2024)

Further, Kenya's 2018 Enterprise Survey states that 47% of firms have female ownership, significantly exceeding the sub-Saharan African average (*see* Figure 3). Despite these gains, alignment with trends in lower-middle-income nations persists; female representation in top managerial roles remains disproportionately low, underscoring persistent structural barriers in leadership hierarchies.

Figure 3: Female participation in Employment, Top Management, and Ownership (%), 2018



Source: The World Bank, Enterprise Surveys, Kenya 2018: Country Profile

2.6.1 The Informal Economy

Kenya's informal sector remains the primary driver of employment, absorbing 84.1% of the workforce outside small-scale agriculture and pastoralism (KNBS *Economic Survey*, 2023). The informal economy is heavily concentrated in trade, manufacturing, and transport. In 2022, Wholesale and Retail Trade, Hotels, and Restaurants dominated with 9.3 million workers (58.3% of informal jobs), followed by Manufacturing (3.2 million jobs) and Transport and Communications (444,900 jobs). Geographically, urban areas accounted for 41.1% of informal employment (6.6 million jobs), reflecting the clustering of informal trade and services in cities, while rural areas hosted 9.4 million informal workers, predominantly engaged in small-scale manufacturing and agriculture-linked activities (KNBS *Economic Survey*, 2023). Gender disparities further compound vulnerabilities within the informal sector. Women face systemic barriers, including restricted access to credit and disproportionate unpaid care responsibilities, which confine them to low-productivity, low-earning roles. This perpetuates cyclical poverty and limits their upward mobility within the informal economy.

Kenya's persistently high informal employment rate—which remains resistant to decline—poses a significant challenge to achieving SDG 8.3.1 (promoting formalization and decent work). Despite policy efforts, informal labor still dominates the economy, reflecting systemic barriers to formalization. However, incremental progress is evident: initiatives such as the National Hospital Insurance Fund have expanded social protection coverage to informal workers, with affiliated members rising steadily (KLMP, 2024). A notable development within the informal economy is the rapid growth of the gig sector, which employs over 100,000 Kenyans in ride-hailing, delivery services, and online freelancing. While this sector provides flexible income opportunities, it operates outside formal regulatory frameworks, leaving workers without job security, benefits, or legal protection. Gig workers experience volatile earnings, unpredictable workloads, and high-pressure conditions, mirroring broader informal sector vulnerabilities.

Kenya's informal economy currently lacks a dedicated legal or policy framework to institutionalize tripartite social dialogue, which would formally integrate workers, employers, and government in decision-making processes. However, the Kenya National Federation of *Jua Kali* Associations [KNFJKA]—representing the informal *Jua Kali* (artisan) sector—has spearheaded advocacy efforts to address this gap. KNFJKA has pushed for amendments to the Labor

Institutions Act of 2007 to include informal sector representation in the tripartite structure of the National Labor Board, arguing for recognition based on enterprise characteristics rather than traditional formal employment criteria (COTU-Kenya, 2024). In parallel, KNFJKA developed an Informal Sector-driven Transformation Strategy to mainstream informality into national development agendas. Responding to these calls, the government established an Informal Sector Transformation Unit under the Office of the Deputy President in January 2024. This initiative includes a Technical Working Group, comprising government agencies, the ILO, and KNFJKA representatives, to facilitate national dialogue on formalizing informal enterprises and advancing inclusive labor policies (COTU-Kenya, 2024).

Trade unions and employers' organizations in Kenya are increasingly targeting the informal economy as a strategic frontier for membership expansion. For instance, the COTU-Kenya has initiated efforts to organize informal workers through sector-specific affiliates representing market vendors, beauty professionals, drivers, gig workers, and other precarious laborers. Through Memorandums of Understanding, these affiliates collaborate with informal economy associations to fight for labor rights, improve working conditions, and enhance access to essential services such as healthcare and financial inclusion (KLMP, 2024). Complementing these efforts, the National Industrial Training Authority [NITA] plays a pivotal role in bridging the skills gap between informal and formal labor markets. By certifying prior skills acquired through informal work, NITA enables workers to transition into regulated employment. COTU-Kenya works closely with NITA to align TVET programs with market demands, ensuring curricula address evolving labor needs (KLMP, 2024).

2.6.2 The Formal Sector: Public Sector vs Private Sector

Kenya's formal sector employment trends reveal a complex interplay of growth, sectoral dynamics, and unresolved gender disparities. According to the *KNBS Economic Survey (2023)*, formal sector employment expanded by 3.8%, rising from 2.9 million workers in 2021 to 3.0 million in 2022, driven by moderate job creation in both the public and private sectors. However, persistent gender imbalances—evident in occupational segregation and wage gaps—highlight structural inequities that continue to hinder inclusive labor market participation.

In 2022, Kenya's private sector retained its position as the primary driver of formal economy employment, representing 65.8% of modern sector jobs—a notable increase from 63.9% in 2021 (KNBS *Economic Survey*, 2023). Core industries such as manufacturing, agriculture, and wholesale/retail trade collectively accounted for 43.1% of private sector formal employment. However, growth trajectories diverged sharply across sectors: manufacturing employment rose by 5.1%, down from 6.7% in 2021, a slowdown linked to globalization pressures and competition from lower-cost imports. Conversely, the accommodation and food services sector saw a striking 23.0% employment surge, propelled by the post-pandemic rebound in tourism and hospitality. Despite these gains, private sector job creation declined to 94,500 positions in 2022 from 125,000 in 2021, signaling a deceleration in labor market expansion.

Public sector employment in Kenya experienced modest growth of 1.6% in 2022, a notable deceleration from the 4.4% expansion recorded in 2021. Education and public administration remained the dominant employers, accounting for 42.8% and 35.7% of public sector jobs, respectively, as outlined in the KNBS *Economic Survey (2023)*. County governments emerged as a key contributor to employment growth, adding 4.4% more positions to reach 217,300 workers, while the Teachers Service Commission—the largest public employer—reduced its workforce by 0.3%. Sectoral disparities were evident: transport and storage surged by 12.6%, driven by rail infrastructure investments, while health and social work expanded by 7.4% amid rising healthcare demands. However, overlapping institutional mandates, particularly between the Salaries and Remuneration Commission and county governments, led to jurisdictional disputes over wage determination, undermining cohesive policy implementation (KIPPRA, 2018).

Kenya's labor market exhibits entrenched gender disparities, marked by occupational segregation that confines women to low-productivity, care-oriented roles while men dominate high-productivity sectors. In 2022, men held 87.2% of mining and quarrying jobs, 77.2% of electricity/gas roles, and 77.1% of manufacturing positions. Conversely, women comprised 66.2% of household employment and 53.4% of health/social work roles—sectors characterized by lower wages and rooted in societal caregiving norms (KNBS *Economic Survey*, 2023). Despite marginal growth in female wage employment to 1.15 million, women's earnings averaged just two-thirds of men's wages, a gap exacerbated by unpaid care responsibilities and limited access to high-growth industries (ILO, 2022; KLMP, 2024). Casual employment, which expanded by 1.8%, disproportionately affects women: only 191,200 female casual workers were recorded compared to 325,800 men, reflecting systemic inequities in job security and bargaining power. Even within the formal sector, women remain overrepresented in informal roles (86% nationally), clustered in precarious occupations such as domestic work, retail, and informal manufacturing. This duality—where women dominate caregiving and service roles in both formal and informal spheres—perpetuates cyclical poverty and underscores the need for targeted interventions to dismantle structural barriers to equity.

2.7 Workforce: Population Dynamics

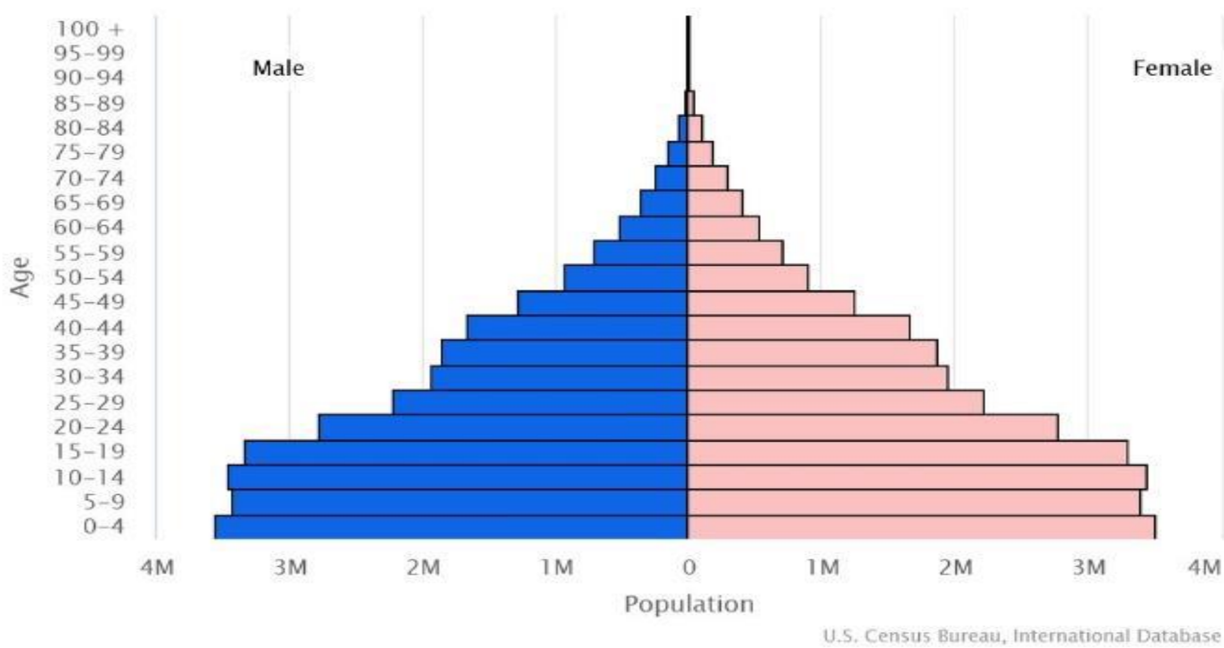
Kenya, a multi-ethnic, multicultural, and multi-religious nation, had an estimated population of 56.1 million in 2024. While the country's population growth rate is decelerating, it remains higher than the sub-Saharan African average, positioning Kenya on a trajectory toward a demographic dividend—a window of economic opportunity arising when the working-age population (15–64 years) surpasses the non-working-age cohort. This shift is reflected in Kenya's shifting age dependency ratio, which declined from 83% in 2011 to 69% in 2022, signaling a gradual transition toward a more productive population structure (Figure 4). Concurrently, Kenya—like much of SSA—is experiencing accelerated growth in its older population (aged 60+). Currently comprising 4.5% of the population, this demographic is projected to double to 9.5% by 2050 (Aboderin & Owii, 2019).

Kenya is undergoing a pivotal demographic transition marked by a pronounced "youth bulge," with individuals aged 15–24 years constituting 32% (10 million) of the working-age population in 2021 (KLMP, 2024). Kenya's government initiatives like the 2019 Kenya Youth Development Policy seeks to enhance youth competitiveness in globalized markets through job creation, digital skills development, and utilizing young people's technological proficiency. However, implementation faces systemic barriers, including fragmented organizational structures and insufficient resource allocation. To address these gaps, the 2022 Youth Development Bill was introduced to codify youth-centric policies into law, intended to harmonize empowerment programs and strengthen institutional frameworks. Despite these efforts, Kenya ranks 143rd out of 183 countries on the 2023 Global Youth Development Index, reflecting persistent challenges in translating policy into equitable outcomes. Nevertheless, this position surpasses regional peers, signaling incremental progress in a complex socioeconomic landscape (KLMP, 2024).

Annually, approximately 800,000 young Kenyans enter the labor market, yet only 15% secure stable or satisfactory employment (ILO, 2023). The majority are relegated to informal, low-income roles lacking social security benefits, reflecting a dual structural challenge: a significant portion of youth lack completed education, while others, despite higher qualifications, encounter a labor market with insufficient formal employment opportunities. This mismatch exacerbates vulnerabilities to unemployment and unmet societal expectations, contributing to psychological distress among graduates pressured to secure white-collar jobs swiftly to support their families.

In 2019, Kenya's NEET rate reached 20%, exceeding that of several neighboring countries (KLMP, 2024), with pronounced gender disparities—24% for women versus 15% for men. This disparity is further compounded by socioeconomic inequities, as youth from lower-income households are disproportionately represented among NEET populations. The economic downturn triggered by the COVID-19 pandemic in 2020 is projected to amplify these challenges, most likely increasing NEET rates. Notably, persistent unemployment has catalyzed a paradigm shift among Kenyan youth. Many are now pursuing TVET institutions to enhance employability, while others are revitalizing interest in agriculture—a trend bolstered by social media's role in reshaping perceptions of the sector (Karuga, 2024).

Figure 4: Population Pyramid based on Age-Sex structure of the population in Kenya, 2023.



Source: Kenya Labor Market Profile (2024) based on Central Intelligence Agency data, Kenya, May 224

2.8 Education System, Structure and Reforms

During Kenya's colonial era (1895–1963), the education system was rigidly stratified along racial lines, perpetuating socioeconomic hierarchies. European settlers received an elite, leadership-oriented education, while Asian communities were trained for middle-tier roles such as artisanship and trade. Africans, however, were confined to substandard schooling focused on manual labor, designed to serve colonial economic interests. This systemic inequity deepened racial divisions, prompting the Phelps-Stokes Commission (1924–25) to recommend nationwide vocational post-primary institutions for Africans, intending to equip them with practical skills (UNESCO, 2005; Muricho, 2023).

Post-independence in 1963, Kenya embarked on sweeping educational reforms to dismantle colonial legacies and align schooling with national development goals. A series of commissions—including the Ominde Report (1964), Bessey Report (1972)**,** Koech Report (1999), Gachathi Report-1976, Mackay Report-1981, Kamunge Report-1988, and Koech Report-1999—restructured curricula to foster unity, economic self-reliance, and civic participation (Muricho, 2023). Influenced by the Addis Ababa Conference (1961), which advocated contextually relevant education across Africa, these reforms prioritized decolonization. The Ominde Commission-1964 was particularly transformative: it abolished racial segregation, introduced the 7-4-2-3 system (mirroring British structures), and reoriented curricula toward Kenya's sociopolitical and economic aspirations (Kaplun, 2019; Mckov, 2022). These efforts underscored education's role as a pillar of nation-building, bridging colonial divides and fostering inclusive progress.

In 1972, Kenya's government established the Bessey Commission to evaluate post-independence curriculum efficacy. The commission's findings revealed systemic shortcomings: secondary education prioritized rote memorization over practical skills, failing to align with national development goals (Momanyi & Rop, 2020). This critique catalyzed structural reforms, including curriculum diversification, and laid the groundwork for the subsequent Gachathi Education Commission in 1976. The Gachathi Commission confronted rising youth unemployment by calling for an enhanced emphasis on Science, Mathematics, and technical-vocational [STEM] subjects to better prepare students for economic participation.

Building on these efforts, the Mackay Report—1981 proposed a transformative overhaul of Kenya's education system. It recommended extending primary education from seven to eight years, transitioning from the 7-4-2-3 model to the 8-4-4 structure—a framework integrating technical and vocational training into primary curricula (Muchunguh, 2021). Implemented in January 1985, these reforms acknowledged that primary education often marked the terminal stage for many learners, necessitating a curriculum focused on market-relevant skills to improve employability. The 8-4-4 system thus emphasized practical competencies, reflecting broader aspirations to bridge education outcomes with labor market demands.

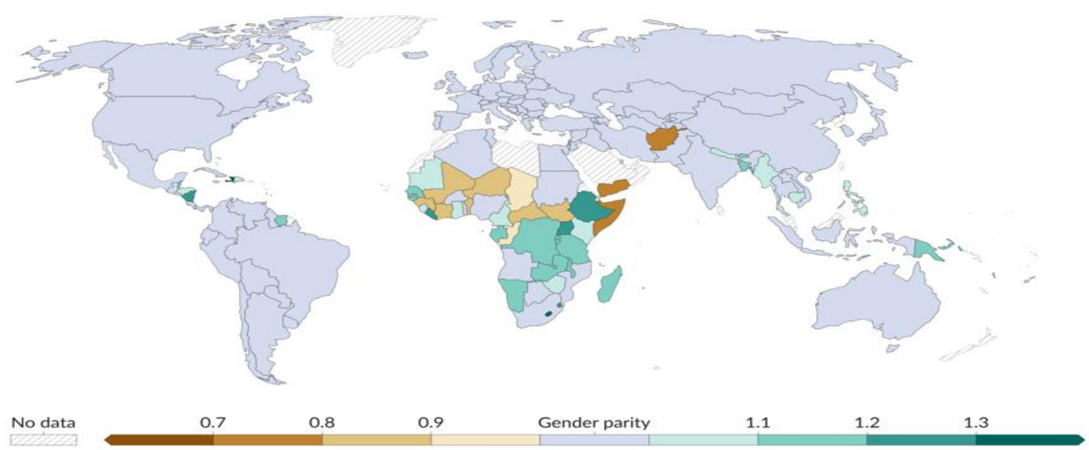
Kenya's 8-4-4 education system, implemented in 1985, structured public education into 8 years of primary school, 4 years of secondary school, and 4 years of university (Muricho & Chang'ach, 2013). However, critics argue that this framework entrenched socioeconomic inequalities, disproportionately excluding low-income students from elite secondary schools. A widening performance gap emerged between public and private institutions, with the latter dominating enrollment in high-ranking schools and securing preferential access to competitive university programs (Amutabi, 2019). To address these disparities, Kenya introduced the Competency-Based Curriculum [CBC] in 2017, following recommendations by the Douglas Odhiambo Taskforce (2012). The CBC adopts a 2-6-6-3 structure: 2 years of pre-primary, 6 years of primary (Grades 1–6), 3 years of junior secondary (Grades 7–9), 3 years of senior secondary (Grades 10–12), and 3 years of tertiary education. This reform emphasizes skill-based learning to enhance equity and adaptability to labor market demands.

Gender parity in education has seen notable progress. While girls' primary enrollment has surged, secondary-level gross enrollment rates still favor males. However, female net enrollment rates have outpaced males since 2010, reflecting targeted interventions like Free Primary Education launched in 2003 and Free Day Secondary Education launched in 2008, which tried to ensure universal access and a 100% primary-to-secondary transition rate (KIPPRA, 2013; Ministry of Education, 2008). By 2020, the transition rate rose to 95%, up from 83.3% in 2018, underscoring the effect of these policies (KNBS, 2021). Consequently, literacy rates now surpass regional averages, with notable improvements in intermediate and advanced education levels among formal employees and, to a lesser extent, the self-employed. Despite these gains, systemic barriers persist, particularly in rural and marginalized communities, necessitating continued reforms to achieve equitable outcomes.

Affirmative action policies and gender mainstreaming initiatives in Kenya have significantly bolstered female enrollment across all educational tiers, including primary, secondary, university, and Technical and TVET institutions. Happily, women's participation in STEM fields has risen, reflecting progress toward bridging gender gaps in high-demand sectors (CUE, 2018). However, socio-cultural barriers—such as child marriages**,** female genital mutilation, and early pregnancies— disproportionately disrupt girls' education. Additional obstacles include children assuming caregiving roles due to parental absence, overcrowded classrooms, uneven infrastructure, weak coordination between national and county governments hinder equitable access to quality education (Republic of Kenya, 2019).

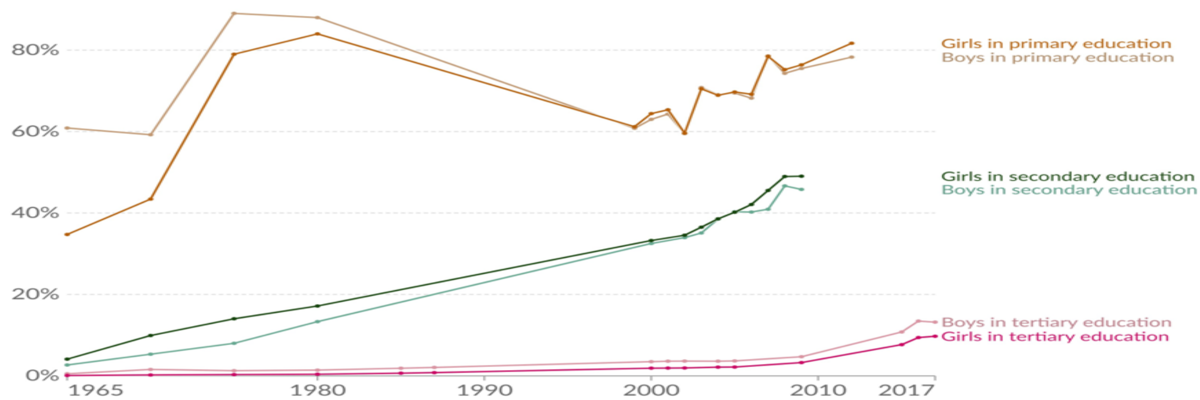
Enrollment data underscores both progress and disparities. According to the KNBS *Economic Survey* (2022), primary school enrollment grew by 1.1% between 2020 and 2021, reaching 10.3 million students, with girls' enrollment rising slightly faster (1.3%) than boys' (1.0%). At the secondary level, girls have consistently outnumbered boys since 2019, signaling strides toward gender parity. Tertiary enrollment trends reveal slower growth in universities compared to a surge in TVET institutions, aligning with national priorities to expand technical skills training. Kenya's literacy rate for individuals aged 15+ has also climbed from 72% in 2007 to 82.6% in 2021, surpassing the sub-Saharan African average of 65% and highlighting the country's commitment to educational advancement.

Figure 5: Primary Completion rate, Adjusted Gender Parity Index, 2021



Source of Data: Data from multiple sources complied by the UN (2023).
https://ourworldindata.org/grapher/primary-completion-rate-adjusted-gender-parity-index

Figure 6: Gender gap in primary, secondary and tertiary education, Kenya.



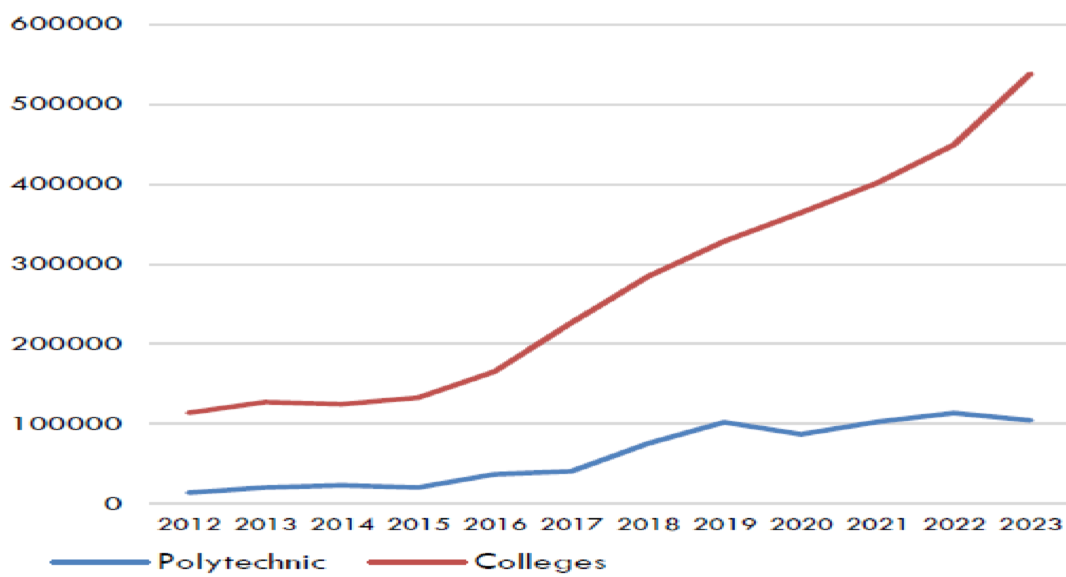
Source: Our World in Data based on Lee and Lee (2016) and UNESCO via World Bank (2023)

Kenya has established a robust legislative and policy framework to advance educational equity, anchored in its 2010 Constitution. This commitment is operationalized through the Basic Education Act, mandating provisions for early childhood and adult education, and the Employment Act of 2007, which enforces employer-funded training programs. A critical issue remains youth unemployment, with one in five Kenyan youth classified as NEET. While the NEET rate for low-educated youth exceeds that of tertiary graduates, the gap between these groups is narrower in Kenya compared to other sub-Saharan nations. Strikingly, young women face higher NEET rates than men at all education levels, underscoring entrenched gender biases. For instance, women with tertiary education still experience a 24% NEET rate compared to 15% for men (ILO, 2023). This disparity reflects systemic labor market failures, where educational attainment alone fails to secure decent work, particularly for women.

Kenya's Vision 2030 and Big Four Agenda prioritize TVET as a pathway to economic growth. The TVET Act of 2013 and TVET Authority provide regulatory oversight, supported by collaborations between national agencies, county governments, and industry stakeholders. Enrollment in TVET institutions surged to 643,000 students in 2023, with a 16% enrollment-to-secondary-school ratio (KNBS *Economic Survey*, 2023). However, the system faces challenges: outdated curricula, weak industry linkages, and limited apprenticeships (500–600 annually for 90,000 TVET students) constrain its impact (World Bank, 2023). Also, societal stigma and an overemphasis on theoretical training—rather than competency-based assessments—limit graduates' employability (TVET Authority, 2024).

Gender disparities permeate the TVET sector. Although female enrollment has risen, women remain underrepresented in high-skill technical fields and face limited access to apprenticeships. For example, only 37% of formal firms offer training programs, with most opportunities concentrated in male-dominated industries. Even when women participate, wage gains are modest; World Bank (2023) studies note that TVET vouchers increased hourly wages only for male wage earners. These inequities are compounded by caregiving responsibilities and cultural norms that prioritize men's economic participation.

Figure 7: Enrollment in TVET institutions in Kenya, 2021-2023



Source: Kenya National Bureau of Statistics, Economic Surveys (various)

3. THEORETICAL FOUNDATIONS

This section offers a theoretical foundation based on neo-classical and human capital models, economic discrimination theory, institutional and labor market segmentation theory, and feminist/gender theory. Here, I establish a robust basis for the empirical studies aligned with the thesis objectives. This multi-theoretical approach ensures that the thesis has diverse perspectives, allowing a comprehensive analysis of gender pay gaps and occupational segregation in Kenya's labor market.

3.1 Neo-classical Economics and Human Capital Model

The concept of human capital encompasses the knowledge, skills, aptitudes, and acquired traits that enhance an individual's productive capacity (Goode, 1959). Rooted in neo-classical economics, the human capital model posits that these attributes generate market returns proportional to labor productivity (Hall & Johnson, 1980). Becker's (1964) seminal framework likens human capital investment to physical capital, emphasizing deliberate resource allocation—such as education or training—to boost future earnings. Becker distinguishes between general human capital (skills transferable across employers) and specific human capital (skills tied to a specific firm/job/occupation). In competitive markets, firms avoid investing in general skills due to the "hold-up problem," where they cannot recoup costs if workers leave (Becker, 1964).

Human capital accumulation occurs through three pathways: formal schooling (full-time education), on-the-job training (employer-provided skill development), and off-the-job training (external programs). Investments are rational only if expected returns—via higher earnings or productivity—exceed opportunity costs, such as foregone income from alternative specializations (Perri, 2003). For instance, pursuing specialized education entails sacrificing potential earnings from other fields, reflecting the trade-offs inherent in human capital decisions. Related to this, Mincer and Polachek (1974) extend this framework to explain gender pay gaps, attributing disparities to differences in productivity shaped by societal roles. Women's disproportionate responsibility for childcare and household labor often leads to fragmented careers, reducing their participation in continuous work and training. This discontinuity diminishes skill retention and discourages employers from investing in female workers, particularly in roles with high turnover costs. Such dynamics foster statistical discrimination, where employers generalize risks across all women due to difficulty distinguishing career-oriented individuals from those likely to exit the workforce (Becker, 1981). Occupational segregation emerges as women move toward jobs requiring less training or offering flexibility, such as roles with high starting wages but low returns on experience. These choices, rational under neo-classical assumptions, stem from balancing market work with unpaid caregiving. Consequently, women accumulate less human capital over time, perpetuating earnings gaps (Polachek, 2006).

Neo-classical theory assumes rational actors in efficient markets: workers maximize earnings based on skills and constraints, while employers optimize productivity and costs (Becker, 1981; Polacheck, 2006). However, gender biases persist. Positions demanding advanced education or on-the-job training are disproportionately offered to men, reflecting employer perceptions of women as higher-cost workers. These perceptions arise from anticipated indirect costs, such as turnover linked to childcare or marriage, which necessitate recurrent recruitment and training (Boll et al., 2017). While women's labor force participation has risen globally, structural inequities endure. For example, roles emphasizing experience or specialized skills remain male-dominated, though this trend is gradually diminishing. Critics argue that the human capital model oversimplifies systemic discrimination, yet its emphasis on productivity differences remains pivotal in explaining wage disparities (Boll et al., 2017).

3.2 Institutional and Labor market segmentation theories

Institutional and labor market segmentation theories challenge the homogeneity assumption of neo-classical economics, emphasizing how political and economic institutions—such as unions and corporations—shape hiring practices, wage determination, and occupational hierarchies. This framework posits that labor markets are divided into distinct segments, each governed by unique rules and attributes (Reich et al., 1973). Unlike human capital models, which focus on individual productivity, segmentation theories highlight systemic inequalities perpetuated by institutional structures (Bauder, 2001).

Central to this theory is the dual labor market dichotomy, distinguishing primary and secondary sectors (Doeringer & Piore, 1971). The primary sector is characterized by stable employment, skill development opportunities, higher wages, and defined career ladders. Jobs here cultivate traits like discipline and adherence to authority (e.g., managerial, or technical roles). The secondary sector is marked by instability, low wages, high turnover, and limited advancement. These roles—often occupied by females, minorities, and youth—lack incentives for long-term commitment (Reich et al., 1973; Doeringer & Piore, 1971). The primary sector is further divided into subordinate jobs which focuses on rule-following and loyalty (e.g., clerical or assembly-line work) while independent primary jobs require creativity, problem-solving, and autonomy (e.g., professions in law or engineering). These roles reward individual achievement but experience higher voluntary turnover.

Labor market segmentation perpetuates gender segregation, with "male" and "female" occupations emerging as distinct segments (Bergmann, 1974). Female-dominated roles (e.g., caregiving, clerical work) are systematically devalued, offering lower wages despite comparable skill requirements. Conversely, male-dominated occupations benefit from broader occupational diversity and higher pay due to reduced competition (Anker, 1997). Institutional biases reinforce this divide. Primary sector firms prioritize continuous work experience and firm-specific skills, favoring men who historically exhibit less career interruption (Barker & Feiner, 2004). Women, often perceived as "second-class employees," face limited access to training and upward mobility, trapping them in secondary or subordinate primary roles. Additionally, employers in the primary sector gravitate toward male candidates, assuming they possess superior qualifications, thereby exacerbating gendered wage gaps (Anker, 1997). The crowding of women into fewer occupations suppresses wages in female-dominated sectors, while male-dominated fields exploit scarcity to command higher pay (Bergmann, 1974). This stratification is reinforced by educational and familial institutions that socialize women into service-oriented roles, further entrenching occupational segregation (Reich et al., 1973).

3.3 Labor Market Discrimination Theories

Economic discrimination, rooted in Becker's (1957) framework on racial bias, occurs when workers with equivalent skills and roles face unequal pay or opportunities solely due to gender (Grybaite, 2006). This shows itself when employers, coworkers, or customers impose costs to avoid associating with marginalized groups, such as women (Shepherd, 2008). Economic discrimination theories are categorized into two models; Competitive models which focus on individual and firm utility/profit maximization and Collective models which involve the mutual discrimination between groups. Competitive models can be further divided into taste and statistical discrimination (Autor, 2003). Becker's (1971) taste discrimination posits that employers derive *disutility* from hiring women, leading them to demand a wage discount to offset perceived inefficiencies. Discriminatory employers hire women only if they accept lower wages or demonstrate higher productivity than men at the same pay level. Similarly, coworkers and customers may exhibit biases: Male workers might demand higher wages to work with female peers, inflating men's earnings (Becker, 1971). Also, customers' reluctance to purchase goods/services from women reduces firms' profitability, incentivizing employers to minimize hiring women (Grybaite, 2006). This model assumes individuals act on prejudicial preferences, willingly bearing costs (e.g., reduced profits) to avoid certain groups (Becker, 1971).

Phelps (1972) introduced statistical discrimination, where employers use group stereotypes to infer individual productivity due to high information costs. For example: Employers assume women, on average, are less career-invested due to anticipated childcare responsibilities. Women are perceived as higher turnover risks compared to men, leading to fewer promotions, or hiring opportunities. This discrimination arises not from malice but from reliance on group averages (e.g., gender) as proxies for unobservable traits like commitment or skill retention. Both models perpetuate gender wage gaps with taste discrimination directly suppressing women's wages through employer biases while statistical discrimination limits women's access to high-productivity roles, reinforcing occupational segregation. In the main, labor market discrimination theories highlight how prejudices (taste) and stereotypes (statistical) distort wage structures and career trajectories. While competitive models emphasize individual choices, they intersect with institutional biases, underscoring systemic barriers to gender equity.

3.4 Feminist/Gender Theory

Feminist/gender theory claims that patriarchal structures and societal norms shape women's disadvantaged position in the labor market, extending beyond economic variables to encompass social and familial dynamics. Central to these theories is the premise that women's subordinate status in both society and the household perpetuates systemic inequalities (Phillips & Taylor, 1980; Anker, 1997; Figart, 2005). The entrenched division of labor—where caregiving and domestic duties are deemed primarily women's responsibility—restricts their ability to accumulate human capital. For instance, girls often receive less education than boys, particularly in technical or scientific fields, reinforcing the perception that women require fewer labor market skills. These social expectations also explain why women frequently exit the workforce earlier or take career breaks, resulting in fragmented work experience and diminished earning potential (Anker, 1997).

Occupational segregation by gender is further exacerbated by gender stereotyping, which aligns "female" occupations with societal assumptions about women's roles and capabilities. Anker (1997) emphasizes that stereotypes influence both employer preferences and women's own labor market decisions, shaping the types of jobs deemed appropriate for women. For example, roles emphasizing nurturing or flexibility—such as part-time work or jobs with adaptable hours—are often labeled as "female" due to their perceived compatibility with caregiving responsibilities. This stereotyping not only limits women's access to higher-paying, male-dominated fields but also reinforces their economic marginalization.

Feminist theories intersect with neo-classical human capital models in acknowledging the flexibility of "female" occupations. Both frameworks recognize that women may gravitate toward jobs offering work-life balance to reconcile domestic duties with employment. However, feminist scholarly works diverge in its critique of the underlying causes. While human capital theory attributes occupational segregation to individual preferences and employer rationality, feminist theories highlight how systemic gender norms and institutionalized stereotypes shape these preferences. For instance, flexible working conditions in female-dominated roles may arise not solely from women's choices but from societal labeling of certain jobs as inherently "feminine" (Anker, 1997). This distinction underscores the tension between agency and structural constraint: women may seek flexible roles to manage household demands, yet these roles are often devalued and underpaid due to gendered assumptions.

3.5 Chapter Conclusion

This chapter uses a multifaceted theoretical landscape to unravel the persistent gender pay gaps and occupational segregation in Kenya's labor market, drawing on four interconnected frameworks. At its core lies the neo-classical and human capital model which posits that earnings disparities stem from differential investments in human capital. Becker distinguishes between *general human capital*—skills transferable across employers—and *specific human capital*—skills tied to a single firm. Women, burdened by societal expectations of caregiving and domestic labor, often experience fragmented careers, reducing their access to continuous education and on-the-job training. This discontinuity not only diminishes their skill retention but also fuels *statistical discrimination*, where employers generalize turnover risks across all women, assuming lower productivity due to anticipated career breaks. While the model emphasizes rational investment choices, it overlooks structural barriers that disproportionately constrain women's opportunities.

Complementing this perspective, institutional and labor market segmentation theories challenge the neo-classical assumption of homogeneous markets. The theory delineate a dual labor market: the *primary sector*, characterized by stability, skill development, and higher wages, is dominated by men, while the *secondary sector*, marked by instability and low pay, traps women, minorities, and youth. Institutional biases further entrench this divide, as female-dominated roles (e.g., caregiving, clerical work) are systematically devalued despite comparable skill requirements. Educational and familial institutions socialize women into service-oriented roles, reinforcing occupational segregation and suppressing wages in female-dominated sectors.

Labor market discrimination theories continue this analysis by exposing how biases permeate hiring and wage-setting practices. The *taste discrimination* model reveals how employers, coworkers, or customers impose costs to avoid associating with women, demanding wage discounts, or shunning their services. At the same time, *statistical discrimination* shows how employers rely on gender stereotypes—such as assumptions about childcare-related absenteeism—to infer productivity, limiting women's access to high-paying roles. These discriminatory practices intersect with institutional segmentation, perpetuating a cycle of marginalization.

Next, feminist/gender theory contextualize these dynamics within patriarchal power structures. The theory argues that societal norms relegating women to caregiving roles restrict their human capital accumulation, as girls receive less education in technical fields and women face career interruptions. Feminist scholarship critiques the human capital model's focus on individual choice, emphasizing instead how systemic *gender stereotyping* labels flexible, part-time roles as inherently "feminine," relegating women to underpaid sectors. While acknowledging overlaps with neo-classical theories on occupational flexibility, feminist frameworks emphasize the need to dismantle institutionalized inequities through transformative policies.

In the main, the human capital model explains productivity disparities but neglects institutional barriers, which segmentation and discrimination theories starkly expose. Feminist theories place these barriers within patriarchal systems, advocating holistic interventions—from anti-discrimination legislation to societal norm shifts—to address Kenya's labor market inequities.

4. RESEARCH METHODOLOGY: DECOMPOSITION METHODS

4.1 Introduction

Research consistently attributes gender earnings disparities to two key factors: inequalities in human capital endowments (e.g., education, work experience) and discriminatory labor market practices, which manifest as unequal treatment or differing returns to comparable skills (Neuman & Oaxaca, 2004; Fortin et al., 2009, 2018). To quantify these gaps, the Oaxaca-Blinder (O-B) decomposition method—pioneered by Oaxaca (1973) and Blinder (1973)—serves as the cornerstone of empirical analysis. This methodology decomposes average earnings differences into two components: The *explained differences* are attributable to observable characteristics (e.g., education, experience) while the *unexplained differences* reflects disparities in returns to these characteristics, often interpreted as a measure of wage discrimination. The "*unexplained*" component, termed the wage structure effect, captures the hypothetical earnings gap that would persist even if men and women had identical human capital endowments. The O-B framework assumes a counterfactual scenario where a non-discriminatory wage structure replaces the current discriminatory one. In such a scenario, men and women would earn equally for equivalent skills and roles. However, under ideal conditions, discriminatory practices inflate men's earnings while suppressing women's, creating a measurable gap between actual wages and this equitable benchmark (Oaxaca, 1973; Blinder, 1973).

4.2 The Oaxaca-Blinder Decomposition (Baseline model)

To contextualize the Oaxaca-Blinder wage decomposition, it is essential to first explore the theoretical foundation laid by Mincer (1974), which models earnings as a function of human capital endowments. Mincer's framework posits that variations in individuals' earnings profiles stem from differences in human capital attributes, such as education, labor market experience, and innate abilities. Mincer's earnings function conceptualizes income as dependent on human capital traits and a set of control variables that capture individual and job characteristics. For simplicity, assuming a semi-logarithmic earnings equation, the income of an individual *i* can be expressed as follows:

$$lnW_i = \beta 0 + \beta_i X_i + \varepsilon_i, \qquad (4.1).$$

where

- lnW_i is the natural logarithm of earnings of individual i (observed only for waged workers),

- X_i represents the vector of observable characteristics including job characteristics and human capital elements (e.g., education, age, potential work experience, household head, marital status, employment sectors, occupations, industry, urban/rural location, etc.)
- β_i is the coefficient of each of the individual characteristics X,
- α_i is the coefficient of the firm- specific control variables, and
- ε_i is the stochastic term which has zero expected value.

Let $\bar{X}$ represent the vector of average values for individual characteristics—such as education, experience, and marital status—that influence labor productivity. Let $\hat{\beta}$ denote the estimated coefficients for these characteristics, derived from the Ordinary Least Squares (OLS) estimation of the Mincer earnings equation. Consequently, the average logarithm of earnings (ln$\bar{W}$) can be estimated by evaluating the fitted values at the "means" of the explanatory variables, expressed as $\bar{X}\hat{\beta}$ for the entire working population. This implies that the logarithmic equation for average earnings can be written as:

$$ln\bar{W} = \bar{X}\hat{\beta} \qquad (4.2).$$

The Oaxaca-Blinder decomposition builds on Mincer's (1974) earnings function by estimating separate earnings values for men and women within the sample. Once these have been calculated, the fitted values of earnings for both groups can be calculated using logarithmic notation. Subsequently, the fitted values in Equation (3.2), evaluated at the "means" of the explanatory variables for men and women, can be expressed as:

$$ln\bar{W}_m = \bar{X}_m\hat{\beta}_m \qquad for\ men \qquad (4.3).$$

$$ln\bar{W}_f = \bar{X}_f\hat{\beta}_f \qquad for\ women, \qquad (4.4).$$

where ln$\bar{W}_m$ represents the logarithm of average earnings for men, and ln$\bar{W}_f$ denotes the logarithmic notation for average earnings for women. The terms $\bar{X}_m\hat{\beta}_m$ and $\bar{X}_f\hat{\beta}_f$ represent the fitted values for men and women, respectively. By subtracting the fitted values in Equation (3.4) from those in Equation (4.3), the overall gender pay gap can be expressed as follows:

$$ln\bar{W}_m - ln\bar{W}_f = \bar{X}_m\hat{\beta}_m - \bar{X}_f\hat{\beta}_f, \qquad (4.5).$$

Here, $\bar{X}_m$ and $\bar{X}_f$ represent the vectors of the "means" of explanatory factors in the earnings equations for men and women, respectively, while $\hat{\beta}_m$ and $\hat{\beta}_f$ denote the parameter estimates derived from the male and female earnings structures. By adding and subtracting the term $\bar{X}_m\hat{\beta}_f$ to the right-hand side of Equation (4.5), we obtain:

$$ln\bar{W}_m - ln\bar{W}_f = \bar{X}_m\hat{\beta}_m - \bar{X}_m\hat{\beta}_f + \bar{X}_m\hat{\beta}_f - \bar{X}_f\hat{\beta}_f \qquad (4.6).$$

By collecting and factoring like terms, Equation (3.6) can be decomposed into two distinct components: the **"**explained**"** and the "unexplained" portions of the total gender pay gap. The explained component captures the share of the earnings disparity attributable to differences in observable human capital characteristics, such as education and experience. In contrast, the unexplained component reflects the portion of the earnings gap linked to unobservable factors, including discriminatory practices that influence the returns to observable factors. Thus, Equation (3.6) can be expressed as the sum of these two components:

$$ln\bar{W}_m - ln\bar{W}_f = \bar{X}_m\left(\hat{\beta}_m - \hat{\beta}_f\right) + \hat{\beta}_f\left(\bar{X}_m - \bar{X}_f\right) \qquad (4.7).$$

$$ln\bar{W}_m - ln\bar{W}_f = \bar{X}_f\left(\hat{\beta}_m - \hat{\beta}_f\right) + \hat{\beta}_m\left(\bar{X}_m - \bar{X}_f\right) \qquad (4.8).$$

Equations (4.7) and (4.8) break down the gender earnings gap into two components: The explained component, which reflects differences in observable characteristics (e.g., education, experience), captured by the second terms of the equations. These terms are evaluated using female returns $\hat{\beta}_f(\bar{X}_m - \bar{X}_f)$ in Equation (4.7) and male returns $\bar{X}_m(\hat{\beta}_m - \hat{\beta}_f)$ in Equation (4.8). The unexplained component, which captures disparities in returns to observed characteristics, is attributed to discriminatory practices and unobservable factors. This component is represented by the first terms of the equations, evaluated at the "mean" set of male and female characteristics. Specifically, Equation (4.7) decomposes the average earnings inequality into: A portion attributable to differences in human capital endowments, estimated using female returns $\hat{\beta}_f(\bar{X}_m - \bar{X}_f)$ and a portion linked to variations in returns to observable factors, estimated at the mean set of male characteristics $\bar{X}_m(\hat{\beta}_m - \hat{\beta}_f)$. This decomposition implies that the male wage structure is treated as the non-discriminatory benchmark, and a portion of the earnings gap arises from preferential treatment or nepotism favoring male workers.

Building on this, Equation (4.8) decomposes the mean gender pay gap into two components: a portion attributed to differences in human capital characteristics and other observable factors, estimated using male returns $\hat{\beta}_m(\bar{X}_m - \bar{X}_f)$ and a portion linked to variations in returns to human capital endowments, estimated via the mean set of female characteristics $\bar{X}_f(\hat{\beta}_m - \hat{\beta}_f)$. This decomposition implies that the female wage structure is treated as the non-discriminatory benchmark, and the gender earnings gap arises partly from favoritism toward male workers and prejudice against female workers. Oaxaca (1973) referred to this ambiguity as the *Index Problem*, drawing a parallel to the calculation of index numbers. The core issue lies in determining whether the male advantage or the female disadvantage should be considered the non-discriminatory wage structure. Due to this uncertainty, Oaxaca estimated both specifications—Equations (3.7) and (3.8)—as wage gap decomposition equations. By doing so, he defined a range within which the true value of the discrimination component lies (Oaxaca, 1973).

In their seminal work, Oaxaca (1973) and Blinder (1973) identified the terms $\hat{\beta}_m(\bar{X}_m - \bar{X}_f)$ and $\hat{\beta}_f(\bar{X}_m - \bar{X}_f)$ as the explained portion of the gender pay gap. These terms quantify the average earnings difference women would experience due to variations in human capital endowments (e.g., education, experience) and other labor market observable factors compared to their male counterparts. On the other hand, the terms $\bar{X}_m(\hat{\beta}_m - \hat{\beta}_f)$ and $\bar{X}_f(\hat{\beta}_m - \hat{\beta}_f)$ measure the unexplained portion of the pay gap, reflecting differences in returns to productivity attributes. In absolute terms, these latter terms represent the amount by which women earn less than men, or conversely, the amount men would earn more than women if they shared the same human capital characteristics. The unexplained portion captures the earnings disparity that cannot be attributed to differences in observable productivity traits but instead stems from discriminatory practices and other unobservable factors in the labor market.

Oaxaca and Blinder (1973) used the male advantage or female disadvantage wage structures to compute gender earnings inequality, leading to the "index problem." This problem arises when it is unclear which group—men or women—should be considered disadvantaged or favored, complicating the determination of a non-discriminatory wage structure. To address this ambiguity, Rubin et al. (1985) argued that groups with distinct combinations of individual characteristics are not directly comparable. This insight necessitated an extension of the Oaxaca-

Blinder decomposition method, refining its ability to account for the complexities of labor market discrimination.

4.3 The Oaxaca-Blinder variants

The O-B decomposition operates on the assumption that, in a non-discriminatory labor market, women would earn a salary based on the same wage structure as men, and men would earn a salary based on the same wage structure as women (Blinder, 1973; Oaxaca, 1973). Discrimination, therefore, manifests as a scenario where men earn more, and women earn less than they would under equitable conditions. However, interpreting the decomposition results involves inherent complexities. The explained component of the gender pay gap estimates what women would earn if they were compensated according to the male wage structure, or what men would earn under the female wage structure. However, this component does not account for the hypothetical wage structure that would exist in the absence of discrimination.

A key challenge lies in the choice of the reference wage structure (male or female) used in the decomposition, as this choice can significantly influence the results. There is no inherent preference for one structure over the other, leading to the index problem—a central issue in decomposition literature. Cotton (1988) and Neumark (1988) critiqued the assumption that the female wage structure represents a non-discriminatory benchmark, arguing that this approach weakens the case for wage equality because it implies women's earnings remain unchanged. Conversely, using the male wage structure as the non-discriminatory standard suggests that men's incomes would remain unaffected by shifts toward wage equality, which Cotton (1988) contested. He argued that in discriminatory labor markets, the disadvantaged gender (typically women) is systematically devalued, while the favored gender (typically men) is overvalued.

Neumark (1988) expanded on the discussion by proposing that employers may engage in nepotism toward men or discrimination against women. Under nepotism, women are paid a fair wage, while men receive overpayment. In this scenario, the coefficients derived from women's earnings functions can be used to estimate the non-discriminatory wage structure. Conversely, under discrimination, men are paid a fair wage, while women are underpaid, and the coefficients from men's earnings functions can serve as the basis for estimating the non-discriminatory wage structure. In practice, employers may simultaneously practice both nepotism and discrimination, complicating the determination of a fair wage structure. Neumark (1988) addressed this by assuming that employers' preferences depend solely on the proportion of men and women employed, with homogeneous preferences of degree zero. Under this assumption, the non-discriminatory wage structure (β^*) can be estimated by averaging the male and female wage structures using an earnings function derived from a pooled sample of both men and women.

In contrast to the O-B decomposition, Neumark's (1988) approach assumes that, in the absence of discrimination, men and women would share a similar wage structure, rather than having distinct structures. This key distinction allows Neumark's method to resolve the index number problem, which arises from the ambiguity in choosing a non-discriminatory wage structure. Additionally, Neumark's framework decomposes the unexplained component—often termed the discrimination or treatment component—into two parts: the advantages experienced by the favored group (typically men) and the disadvantages faced by the discriminated group (typically women). These components are measured relative to the wage structure that would exist in a non-discriminatory labor market.

The O-B decomposition challenges Becker's (1971) foundational assumption about labor markets, specifically the notion of a non-discriminatory wage structure. Becker argued that in a perfectly competitive labor market free from discrimination, men and women would be treated as perfect substitutes in production. Under such conditions, earnings inequality would arise solely from differences in human capital endowments, and equal labor characteristics would result in equal earnings. Thus, in the absence of discrimination, earnings equality between men and women would prevail, eliminating the index problem. To address the index problem, let β^* represent a non-discriminatory wage structure that ensures equality for both men and women in a discrimination-free labor market. This implies that, under β^**, men and women with equal human capital endowments would receive the same earnings. In other words,* $\beta^* = \hat{\beta}_m = \hat{\beta}_f$, where $\hat{\beta}_m$ and $\hat{\beta}_f$ denote the male and female wage structures, respectively. The goal of introducing β^* is to redefine the wage decomposition components, ensuring they reflect a truly equitable wage structure and providing a more accurate measure of discrimination in the labor market.

In his seminal work, Becker (1971) introduced the concept of a competitive labor market discrimination coefficient (Y)**,** defined as the difference between the observed earnings ratio and the income ratio that would exist in the absence of discrimination. Building on this, Oaxaca (1973) formalized Becker's discrimination coefficient as follows:

$$Y = \frac{\bar{W}_m / \bar{W}_f - MP_m / MP_f}{MP_m / MP_f}, \tag{4.9}$$

In this framework, $\bar{W}_m$ / $\bar{W}_f$ represents the observed average earnings ratio of men to women, while MP_m / MP_f denotes the ratio of the marginal products of men and women. In the absence of discrimination, the ratio of marginal products equals the observed earnings ratio, implying:

$$Y = \frac{\bar{W}_m / \bar{W}_f - MP_m / MP_f}{MP_m / MP_f} = 0, \tag{4.10}$$

Rewriting Equation (4.10) in terms of the earnings ratio of men to women, we obtain:

$$Y = \frac{\bar{W}_m/\bar{W}_f}{MP_m/MP_f} - \frac{MP_m/MP_f}{MP_m/MP_f}, \tag{4.11}$$

$$\frac{\bar{W}_m/\bar{W}_f}{MP_m/MP_f} - 1 = Y, \tag{4.12}$$

Simplifying Equation (4.11), we arrive at:

$$\frac{\bar{W}_m/\bar{W}_f}{MP_m/MP_f} = Y + 1, \tag{4.13}$$

Multiplying both sides by the ratio of marginal products, we get:

$$\bar{W}_m/\bar{W}_f = (MP_m/MP_f) * (Y + 1), \tag{4.14}$$

Finally, expressing Equation (4.12) in logarithmic notation to represent the average earnings difference between men and women, we obtain:

$$ln\bar{W}_m - ln\bar{W}_f = lnMP_m - lnMP_f + \ln(Y + 1) \tag{4.15}$$

Equation (4.15) says that the total gender pay differential (ln$\bar{W}_m$ - ln$\bar{W}_f$) consists of two components: a portion attributable to differences in the marginal productivity of men and women (lnMP_m - lnMP_f), representing the explained portion of the gender pay gap and a portion [ln(Y+1)] that cannot be accounted for by differences in human capital characteristics, reflecting discriminatory practices in the labor market, which is termed the “treatment” or “unexplained” component.

It should be noted that equations (4.5), (4.7), (4.8), and (4.15) are equivalen**t**, as they all measure the overall gender earnings gap**.** Specifically: the second components of equations (4.7) and (4.8) capture the portion of the pay gap due to differences in productivity traits, aligning with the explained component (lnMP_m - lnMP_f) in Equation (4.15). The first components of equations (4.7) and (4.8) measure the portion of the earnings gap due to differences in returns to productivity traits, reflecting discriminatory practices and other unobservable factors. These align with the unexplained component [ln(Y+1)] in Equation (4.15). If a non-discriminatory wage structure (β^*) exists in the absence of discrimination, then $\beta^* = \hat{\beta}_m = \hat{\beta}_f$, eliminating the distinction between male advantage and female disadvantage (where $\hat{\beta}_m > \hat{\beta}_f$). Under this assumption, Equation (3.7) can be rewritten as:

$$ln\bar{W}_m - ln\bar{W}_f = \bar{X}_m(\hat{\beta}_m - \beta^*) + \beta^*(\bar{X}_m - \bar{X}_f) \quad (4.16).$$

The estimation of the total earnings gap in Equation (4.16) includes the component $\beta^*(\bar{X}_m - \bar{X}_f)$, which captures differences in observable productivity characteristics evaluated under a hypothetical non-discriminatory labor market. Specifically: the term $\beta^*\bar{X}_m$ represents the earnings men would receive in a non-discriminatory wage structure, based on their human capital productivity. In contrast, the term $\hat{\beta}_m\bar{X}_m$ in Equation (4.7) reflects men’s current earnings, which include the effects of favoritism or discriminatory behavior in the labor market. This implies that the earnings men receive under the current discriminatory wage structure ($\hat{\beta}_m\bar{X}_m$) exceed what they would earn in a non-discriminatory scenario ($\beta^*\bar{X}_m$). The difference between these two terms quantifies the advantage men gain from discriminatory practices. Mathematically, this can be expressed as:

$$\sum \hat{\beta}_m\bar{X}_m - \sum \beta^*\bar{X}_m = \sum \bar{X}_m(\hat{\beta}_m - \beta^*) \quad (4.17).$$

Consequently, in a non-discriminatory wage structure, where $\beta^* = \hat{\beta}_m = \hat{\beta}_f$ (instead of $\hat{\beta}_m > \hat{\beta}_f$), Equation (4.8) can be rewritten as:

$$ln\bar{W}_m - ln\bar{W}_f = \bar{X}_f(\beta^* - \hat{\beta}_f) + \beta^*(\bar{X}_m - \bar{X}_f), \qquad (4.18).$$

where the term $\beta^*\bar{X}_f$ represents the earnings women would receive in the absence of discrimination, based on their observable productivity characteristics. This contrasts with the term $\hat{\beta}_f\bar{X}_f$ in Equation (4.8), which reflects women's current earnings under discriminatory labor market conditions. Thus, the earnings women would receive in a non-discriminatory scenario exceed what they currently earn under discrimination. This difference can be expressed as:

$$\sum \beta^*\bar{X}_f - \sum \hat{\beta}_f\bar{X}_f = \sum \bar{X}_f(\beta^* - \hat{\beta}_f) \qquad (4.19).$$

From equations (4.17) and (4.19), it is evident that the average gender pay gap can be decomposed into three components, unlike the two components in the original Oaxaca-Blinder decomposition (equations 4.7 and 4.8). This refined approach, introduced by Neumark (1988), precisely expresses the gender pay gap as:

$$ln\bar{W}_m - ln\bar{W}_f = \sum \beta^*(\bar{X}_m - \bar{X}_f) + \sum \bar{X}_m(\hat{\beta}_m - \beta^*) + \sum \bar{X}_f(\beta^* - \hat{\beta}_f) \qquad (4.20).$$

The augmented O-B wage decomposition method divides the treatment or return component into two parts: one reflecting the advantage of being a male worker and the other capturing the disadvantage faced by women. Specifically: the *first Component* $\sum\beta^*(\bar{X}_m - \bar{X}_f)$ represents the portion of the gender earnings gap attributable to differences in observable characteristics when evaluated under a hypothetical non-discriminatory labor market. It reflects the earnings gap that would exist solely due to variations in productivity individual traits. The *second component* $\sum\bar{X}_m(\hat{\beta}_m - \beta^*)$ captures the extent to which men's productivity characteristics are overvalued in the labor market, resulting in a male advantage. It quantifies the favorable treatment or bias toward men in terms of how their productivity traits are rewarded. And, the *third component* $\sum\bar{X}_f(\beta^* - \hat{\beta}_f)$ measures the extent to which women's characteristics are undervalued, leading to a female disadvantage. It reflects the unfavorable treatment or bias against women in terms of how their productivity traits are compensated.

While Neumark's (1988) decomposition method provides a more nuanced approach, it is not without criticism. A key concern is the assumption that employers care only about the ratio of men and women employed, which lacks empirical support. As a result, using the pooled coefficient as an estimator for the non-discriminatory wage structure is not clearly justified (Appleton et al., 1999). To address this limitation, alternative methods were proposed. For instance, Cotton (1988) estimated the non-discriminatory wage structure by weighting the wage structures of men and women based on their respective proportions in the sample.

It is important to note that, in the original O-B decomposition method, the term $\sum \bar{X}_f \hat{\beta}_m$ in Equation (4.8) represented the discriminatory component, where women's human capital productivity was evaluated using the male wage structure. This term reflects the earnings women would receive if their productivity endowments were rewarded at the same rate as men's. In contrast, in Equation (4.20), the term $\sum \bar{X}_f \beta^*$represents women's earnings based on their human capital endowments in a hypothetical non-discriminatory labor market, where both men and women receive equal rewards for their productivity.

It should be mentioned that equation (4.8) of the original O-B decomposition tends to overestimate the "true" earnings difference attributable to variations in human capital characteristics, while underestimating the "true" portion of the gender wage gap linked to discriminatory practices (the treatment or unexplained component). Conversely, Equation (4.7) of the original O-B method underestimates the "true" explained component and overestimates the "true" unexplained component of the earnings gap.

The augmented earnings decomposition proposed by Neumark (1988) in Equation (4.20) addresses these issues by further dividing the discriminatory component into two parts using a non-discriminatory wage structure (β^*), which represents the wage structure that would exist in the absence of discrimination. Since β^* is an unobservable vector, it must be estimated within the decomposition framework. There is no consensus in the literature on how to estimate (β^*). However, Reimers (1983) and Cotton (1988) proposed a weighting technique based on the proportions of men and women in the labor force. For a non-random sample, this involves weighting the male and female wage structures according to their respective shares in the population. For a random sample, the weighting is based on the gender distribution observed directly in the sample.

Regardless of the weighting procedure or the type of sample population used, the non-discriminatory wage structure (β^*)—a vector of unobservable characteristics—can be specified as follows:

$$\beta^* = P_m\beta_m + P_f\beta_f, \tag{4.21}$$

where P_m and P_f represent the proportions of men and women, respectively, in the labor force sample. The robustness of the augmented wage decomposition (Neumark, 1988; Cotton, 1988; Reimers, 1983) depends on the accurate estimation of (β^*), which relies on two key assumptions. First, there is earnings adjustment in the absence of discrimination where in a discrimination-free labor market, men would earn less on average than they currently do, while women would earn more than their present earnings. This implies that the favoritism toward men and the disadvantage faced by women would be eliminated or reduced. Mathematically, this is expressed as: $\sum \beta_m \bar{X} > \sum \beta^* \bar{X} > \sum \beta_f \bar{X}$. The second assumption is about the market-driven wage structure where in the absence of discrimination, the wage structure would be determined solely by market forces that currently influence the earnings of men and women. Therefore, the non-discriminatory wage structure β^* is a linear function of the current average earnings structures of men (β_m) and women (β_f) under discriminatory conditions.

4.4 Selectivity Bias Correction: The Heckman and BFG selection models

The issue of selectivity bias stems from Heckman's (1979) seminal work, which highlighted how sample selection arises from women's decisions about whether to participate in the labor force. However, Neuman and Oaxaca (2004) expanded on this by identifying two key scenarios where selectivity bias can occur: first, at the point of labor force entry (the decision to join or not join the workforce) and second at the point of occupational choice (the selection of a specific occupation). Occupational selectivity bias significantly affects earnings inequality because different occupations offer distinct remuneration packages (wage offers) and exhibit varying levels of discriminatory practices. Additionally, bias arises because earnings data typically reflect only those individuals currently engaged in income-generating activities, excluding others who may be seeking employment, receiving in-kind payments, or working without pay in domestic roles, such as childcare and household labor (Neuman & Oaxaca, 2004). As a result, using the

OLS technique to estimate earnings functions leads to biased and inconsistent parameter estimates (Heckman, 1979).

The Heckman model addresses selection bias by treating it as a form of omitted variable bias (Heckman, 1979). This bias occurs when the sample of wage-employed individuals is not randomly selected, and it may exhibit specific characteristics. To correct for this, the model incorporates a sample selection term, derived from an equation that estimates the probability of being in wage employment/labor force participation, into the log earnings equation (Equation 4.1). The estimation process involves two stages. In the first stage, the maximum likelihood estimates of probit or multinomial logit models are separately calculated for men and women to model the probability of labor force participation in wage employment (referred to as the selection equation). Then, a selection correction term, known as the inverse Mills' ratio, is included in the log earnings equations for men and women, while assuming joint normality of the error terms in the selection and wage equations. This standard assumption underpins the consistency of the two-step estimator, allowing the inverse Mills ratio to appropriately adjust for selection bias (Heckman, 1979). By augmenting the earnings equations with this term, the resulting OLS estimates become unbiased and consistent. Moreover, to account for potential differences in earnings determinants across employment sectors, earnings equations are estimated separately for three distinct sectors, namely the public sector, the private formal sector, and the informal sector. However, the Heckman two-step estimation procedure has limitations. It does not address another potential source of selection bias that arises when the labor market is segmented or when the dependent variable is categorical.

Economists consistently argue that estimating wage equations using an endogenously chosen sample introduces the risk of selectivity bias, leading to biased parameter estimates in the earnings equation (Reimers, 1988). Since employment choices in the labor market are contingent and non-random, it is essential to correct for selection bias to ensure accurate and unbiased estimators. To address the potential sample selection bias arising from the decision to work in different employment sectors, I employ a variant of Dubin and McFadden's (1984) two-step estimation procedure, known as the Bourguignon-Fournier-Gurgand [BFG] procedure (Bourguignon et al., 2007). This method involves two stages. In the first stage, the maximum likelihood estimates of multinomial logit sectoral choice models are separately calculated for men and women. In the second stage, the selection correction terms are incorporated into each earnings equation. These terms are computed based on the estimated parameters from the multinomial logit sectoral choice models. Specifically, the first step involves estimating the selectivity correction terms from a multinomial logit regression equation, which models the likelihood of an individual *i* being employed in sector j. This is achieved by estimating the following multinomial logit model:

$$E_{ij} = \alpha_{ij} X_{ij} + \mu_{ij} \quad i = 1, 2, \dots\dots\dots\dots, n\,; j = alternative\ sector, \qquad (4.22).$$

In this framework, E_{ij} is a categorical variable representing the sector of employment, where *i* denotes individuals and *j* denotes the specific employment sector an individual is likely to participate in. X_i is a vector of variables expected to influence employment status, α_i represents the parameter estimates associated with X_i, and μ_i is the stochastic error term. By estimating equation (4.22), the selection equation, we obtain the selectivity correction term, which is then incorporated as a regressor into the wage equation (4.23)**.** Following the Durbin-McFadden approach, the probability of a worker belonging to a specific employment category is estimated using a multinomial logistic regression technique (Durbin & McFadden, 1984). For each employment sector choice, the selectivity correction term is computed and added to the structural earnings equations as an additional predictor variable. Thus, after controlling for selection bias, the Mincerian earnings function can be expressed as follows:

$$lnW_i = \beta_0 + \sum \beta_i X_{in} + \sum \theta_i \lambda_{ik} + \varepsilon_i, \qquad (4.23).$$

where lnW_i represents the natural logarithm of earnings, X_{in} is a vector of explanatory variables (where *i = 0, 1, 2, ..., n*), λ_{ik} is the vector of the selectivity bias correction term generated for each employment choice, α_i represents the vector of parameters to be estimated associated with X_{in}, θ_i denotes the vector of coefficients for the selection bias correction term, and ε_i is the stochastic term. By incorporating the selectivity bias correction term, the augmented wage decomposition Equation (4.20) can be rewritten to account for sample selection bias as follows:

$$ln\bar{W}_m - ln\bar{W}_f = \sum \beta^* \left(\bar{X}_m - \bar{X}_f\right) + \sum \bar{X}_m \left(\hat{\beta}_m - \beta^*\right) + \sum \bar{X}_f \left(\beta^* - \hat{\beta}_f\right) + \theta_m \lambda_m - \theta_f \lambda_f \qquad (4.24)$$

5. DATA DESCRIPTION, VARIABLES, AND DESCRIPTIVE STATISTICS

In this chapter, I provide an overview of the data concepts and definitions, outline the variables derived from the survey data, and present descriptive statistics from all three empirical studies. This preliminary discussion sets the stage for understanding the data source, key variables, and basic insights that inform the subsequent empirical investigations.

5.1 Data concepts, Definitions, and Variables

I utilized data taken from the 2021 Kenya Continuous Household Survey [KCHS-2021], conducted by the Kenya National Bureau of Statistics. The KCHS-2021 is a nationally representative survey that provides detailed insights into social and economic conditions at various levels, including national, county, urban, and rural areas. Its primary goal is to monitor the socio-economic status of the economically active population. The survey covered 17,042 households, with personal interviews conducted to gather demographic, occupational, and wage information. While the survey included 68,677 individuals (33,392 males and 35,285 females), I focus specifically on individual earnings, limiting the analysis to individuals who are wage-employed. The sample is restricted to workers aged 15 to 65, which aligns with Kenya's working age range. The lower age limit of 15 adheres to the Employment Act of 2007, which prohibits the employment of children under 15 years (Republic of Kenya, 2010), while the upper age limit corresponds to the mandatory retirement age in Kenya.

After applying these restrictions, the final sample consists of 6,653 wage employees, including 4,210 men and 2,443 women, all aged between 15 and 65 years. This observed gender disparity in the final sample (4,210 men vs. 2,443 women) stems from structural barriers shaping women's access to wage employment. While the KCHS-2021 dataset initially included near-equal gender representation (33,392 men and 35,285 women), the thesis's focus on *wage-employed individuals with documented earnings* inherently excluded segments disproportionately affecting women. Within the restricted sample, the youth are defined as individuals aged between 15-34 years are 3,414 (2,142 men, 1,272 women) while older workers (aged 35–65 years) are 3,239 individuals (2,068 men and 1,171 women). The sample is further categorized by employment sector, namely a formal sector which comprises a public sector consisting of 1,229 wage employees and private sector consisting of 747 wage employees. The informal sector consists of 4,677 wage employees.

A key preliminary issue in analyzing the gender pay gap by educational stratification is determining the appropriate educational threshold for categorizing the sample. Studies examining GPG between highly educated and low-educated workers often differentiate between workers with a university degree and those with lower educational attainment (Mussida & Piccha, 2014; Addabbo & Favaro, 2011). In this dissertation, I adopt a different approach by categorizing workers based on compulsory basic education versus higher-level education, in line with Kenya's educational system (Kaplun, 2019; Mckov, 2022; Muchunguh, 2021; Muricho & Chang'ach, 2013). Specifically: low-educated individuals are those who have completed primary, post-primary, or secondary education (compulsory basic education) while highly educated individuals are defined as those who have attained a higher college diploma, bachelor's degree, or postgraduate degree. This categorization aligns more closely with the structure of Kenya's educational system and the occupational opportunities associated with different levels of education, providing a more contextually relevant framework for analyzing earnings disparities by education level.

Based on these considerations, I classify workers with compulsory basic education as "low-educated" and those with at least a post-compulsory school diploma as "highly educated". According to the International Standard Classification of Education, this corresponds to distinguishing between ISCED levels 0–2 (low-educated) and ISCED levels 3–7 (highly educated) (Addabbo & Favaro, 2011). Using this categorization, the KCHS-2021 dataset allows us to create a dummy variable to differentiate between individuals with a completed university degree (ISCED 5–7), who are included in the highly educated group, and those without one. Following this approach, the sample for the analysis of the second objective consists of 1,500 highly educated workers and 5,153 low-educated workers. For the third objective, I utilize the full sample of 6,653 workers, categorizing them into nine occupational groups as defined by the Kenya Standard Classification of Occupations (KeSCO-2022, State Department for Labor and Skills Development). Next, I divide the full sample into urban workers (2,903 individuals) and rural workers (3,750 individuals).

Although the total sample size is relatively small, I apply sampling weights in the decomposition analysis to ensure representativeness, while correcting for county effects. The weighted sample size is estimated at 5,402,634**,** comprising 3,459,173 male employees and 1,943,461 female employees. This weighted sample represents approximately 30 percent of the total employment figure of 19.1 million, as reported in the KNBS *Economic Survey* (2023)**.**

The formal sector in Kenya, often referred to as the modern sector, comprises employment characterized by regulated labor practices, adherence to statutory frameworks, and structured wage systems. It is divided into two primary components: the **public sector** and the **private sector**. The public sector includes government ministries, county governments, parastatal bodies (wholly government-owned corporations) and state-owned agencies where the government holds majority shares, civil service including judiciary, parliament, ministries, and corporations. Key employers in this sector are entities like the Teachers Service Commission, county administrations, and public service institutions such as education, healthcare, and public administration. Employment here is governed by formal contracts, collective bargaining agreements, and statutory benefits, including pension schemes and health insurance. The private sector encompasses industries such as manufacturing, agriculture, wholesale and retail trade, construction, and financial services. Firms in this sector operate under formal registration, comply with labor laws, and contribute to social security systems like the National Social Security Fund. Wage employment in the private sector is marked by structured payroll systems, with earnings often negotiated through CBAs or aligned with gazetted minimum wage standards. Formal employment is distinguished by its inclusion in official records, provision of social protections, and compliance with labor regulations outlined in the Employment Act of 2007 and Labor Relations Act of 2007.

The informal sector constitutes economic activities operating outside formal regulatory frameworks, characterized by lack of registration, unstructured employment terms, and absence of social security contributions. It is the dominant source of employment in Kenya, accounting for approximately 81% of non-agricultural and 97% of agricultural employment. Key features include a predominant small-scale enterprises in trade (e.g., street vendors), manufacturing (e.g., artisanal workshops), transport (e.g., motorcycle taxis), and paid domestic services. Workers include individuals employed in informal private enterprises (commonly referred to as "Jua-Kali" in

Kenya), non-governmental organizations, and domestic workers in private households, and casual workers. The informal jobs lack formal contracts, statutory benefits, and adherence to minimum wage laws. Labor practices are often unregulated, with income variability and limited access to occupational safety measures. The sector thrives due to low entry barriers, reliance on simple technologies, and flexibility, though it faces challenges such as low productivity and vulnerability to economic shocks.

Wage employment refers to work arrangements where individuals receive regular monetary compensation from an employer, typically under formal/informal contractual terms. This entails modern sector employment where employees in both public and private sectors who earn fixed salaries or wages, documented in official records (KLMP, 2024; KNBS *Economic Survey*, 2023). The structure of wage employment is categorized into regular (permanent) and casual (temporary) roles. Regular employees enjoy benefits such as pensions and health insurance in the formal sector, while casual workers sector in the informal often lack such protections despite legal entitlements. Lastly, wages (monthly) refer to income from wage employment, encompassing wages, salaries/earnings received in the past month excluding allowances.

Table 2 lists the main variables used in the analysis, while Table 3 outlines the nine occupational groups defined according to the Kenya Standard Classification of Occupations (KeSCO-2022, State Department for Labor and Skills Development).

Table 2: Definition of Variables

Variable	**Definition**
Age	Age of individual (Continuous variable)
Age 15 – 34 years	1 if age is between 15 years and 34 years (Youth)
Age 35+	1 if age is 35 and above
Married	1 if married, 0 otherwise
Hours of work	Weekly hours of work (continuous)
Female	1 if female, 0 otherwise
Primary	1 if individual with primary education
Post-primary	1 if individual completed post-primary education
Secondary	1 if individual completed secondary education
Diploma	1 if individual completed diploma
Bachelors	1 if individual completed undergraduate degree
Post-graduate	1 if individual completed post-graduate degree
Earnings/wages (monthly)	Monthly earnings in Kenya Shillings (Ksh.)
Log monthly earnings	Natural logarithm of monthly earnings in Ksh.

Labor Union	1 if individual belongs to labor union
Urban	1 if individual lives in urban areas, 0 otherwise
Rural	1 if induvial lives in rural areas, 0 otherwise
Primary sector	1 if industry classification is skilled Agriculture & fisheries
Manufacturing	1 if industry classification is manufacturing
Mining and Extractives	1 if industry classification is mining and extractives
Tertiary sector 1	1 if industry classification is electricity, gas and water supply, construction
Tertiary sector 2	1 if industry classification is wholesale and retail trade, hotels, and restaurants
Tertiary sector 3	1 if industry classification is transport, storage and communications, financial intermediation
Tertiary sector 4	1 if industry classification is real estate, renting and business activities, public administration, compulsory social security
Tertiary sector 5	1 if industry classification is education, health and social work, other community social and personal service activities
Tertiary sector 6	1 if industry classification is private households with employed persons
Household size	Number of household members/number of children in the household (continuous variable)

Source: Author's construction (2024) based on KCHS-2021 data.

Table 3: The Kenya Standard Classification of Occupations (KeSCO-2022)

Occupation Group	**KeSCO Classification**
Major Group ONE (Occ1)	Legislators, Administrators, and Managers
Major Group TWO (Occ2)	Professionals
Major Group THREE (Occ3)	Technicians and Associate professionals
Major Group FOUR (Occ4)	Secretarial, Clerical services, and related workers
Major Group FIVE (Occ5)	Service workers, shop, and market sales workers
Major Group SIX (Occ6)	Skilled Agriculture, Forestry, and Fishery workers
Major Group SEVEN (Occ7)	Craft and related trade workers
Major Group EIGHT (Occ8)	Plant and Machine operators and assemblers
Major Group NINE (Occ9)	Elementary Occupations

Source: Author's construction (2024) based on KeSCO-2022 classifications.

5.2 Descriptive statistics

5.2.1 Gender disparities and the labor market outcomes

Before analyzing earnings and other characteristics of waged employment, it is essential to understand the composition of the weighted sample. Descriptive statistics measures are used to accurately represent the population by gender. Table 4 provides basic labor market indicators for males and females separately. The figures indicate that women face a less favorable labor market position compared to men. Female employment stands at 73.56%, lower than the 80.40% rate for men. However, unemployment rates are similar, with both women and men at 11.1%. Additionally, a larger share of men are engaged in wage employment. Notably, a significantly higher proportion of women (12.44%) than men (4.59%) are involved in home labor, including social reproduction, housework/unpaid domestic responsibilities/family responsibilities—a disparity most likely tied to traditional gender roles and societal expectations. Furthermore, men have a slight advantage in labor market activity rates, as seen in their higher participation in volunteer work and apprenticeships.

Table 4: Labor market outcomes by gender

	Male (%)	Female (%)	Total (%)
Employed (working for pay or profit)	80.40	73.56	77.87
Unemployed (seeking employment)	11.10	11.35	11.19
Home labor/unpaid domestic work	4.59	12.44	7.49
Retired/Income recipients	0.05	0.02	0.04
Volunteer (Job market)	0.06	0.04	0.05
Apprentice/Intern	0.11	0.02	0.08
Total	100.00	100.00	100.00

Source: Author's calculations (2024) based on KCHS-2021 data. Note: Individuals aged 15-65 years. Weighted data

Table 5 lists the characteristics of wage employment, revealing notable gender disparities in its nature and conditions. For men, formal wage employment—comprising both public (12.3%) and private (14.6%) sectors—represents the smallest share of wage-employed individuals. The majority of wage-employed men (73.1%) work in the informal sector. Similarly, for women, the informal sector is the most common form of wage employment, accounting for 65.1% of wage-employed individuals in that sector. This aligns with the KNBS *Economic Survey* (2023), which found that the informal sector constitutes approximately 84% of total employment in Kenya. For women, private formal sector employment makes up 15.6%, while public sector employment represents 19.29%. Comparatively speaking, women are less likely than men to work in the public and private formal sectors as regular full-time, part-time, or seasonal/casual employees. This suggests that men are more actively engaged in the labor market, and formal wage-employed women face less favorable working conditions than their male counterparts.

Table 5: The distribution of waged employment by employment sector and nature of employment

	Male (%)	Female (%)
Public sector	12.30	19.29
Private formal sector	14.64	15.60
Informal sector	73.06	65.11
Regular workers full-time	32.38	37.45
Regular workers part-time	5.23	5.25
Regular workers seasonal	8.64	4.71
Casual workers	53.75	52.60

Source: Author's calculations (2024) based on KCHS-2021 data. Note: Individuals aged 15-65 years. Weighted data

5.2.2 Gender disparities by education

Table 6 presents descriptive statistics on the educational characteristics of wage-employed workers by gender, categorized by employment sector and age cohorts. The results indicate that women generally have a higher distribution of education[2] at advanced levels, suggesting progress toward educational parity. Women appear to have surpassed men in educational attainment across the hierarchy in Kenya. While slightly more men than women have completed basic education (primary, post-primary, and secondary levels), overall, there is gender equality in education among wage-employed workers. Interestingly, a gender gap favoring men with bachelor's degrees persists across all age groups but diminishes among older cohorts. Among younger workers, the largest education gap is observed at the diploma level, though this disparity narrows as education levels increase across all age groups.

Both men and women with higher education levels are more likely to secure better-paid jobs. In the public sector, wage employment is dominated by workers with at least a secondary education. In the private sector, a clear divide exists between the formal and informal segments: the formal sector primarily employs workers with a secondary education and above, while the

[2] Primary education includes standard 1-8 (grade 1–8); Secondary education entails forms 1-4 (grades 9–12); Diploma includes a certificate or diploma course (1-3 years) and higher national diploma course; Bachelors means 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).

informal sector is largely composed of those with a secondary education or below, for both genders. In addition, the private formal and public sectors have a slightly higher proportion of highly educated men compared to women, suggesting that women may face greater competition or barriers in accessing private formal employment. This could stem from factors such as gender biases, occupational segregation, or limited opportunities for women to enter and advance in certain industries or roles. Overall, a slightly higher proportion of all wage-employed workers have attained compulsory basic education[3].

Table 6: The distribution of Education of the waged workers by gender

	Primary		Post-primary		Secondary		Diploma		Bachelors		Post-graduate	
	Men (%)	Women (%)	Men (%)	Women (%)	Men (%)	Women (%)	Men (%)	Women (%)	Men (%)	Women (%)	Men (%)	Women (%)
All waged employees	41.09	39	1.85	1.40	37.82	27.03	11.76	21.62	6.45	8.50	1.03	2.22
Employment sector												
Public sector	5.54	10.56	0.58	1.43	14.58	29.21	49.37	28.16	24.66	27.10	5.28	3.54
Private formal	9.78	18.70	3.79	0.70	22.11	40.45	41.24	23.90	16.69	12.75	6.39	3.49
Informal	58.88	51.73	1.01	2.19	32.64	38.83	6.72	6.02	0.72	1.21	0.03	0.02
Age Cohorts												
15 - 24 years	33.31	38.88	2.93	2.44	42.39	51.31	16.53	6.25	4.74	1.12	0.09	0.0
25 – 34 years	35.64	34.35	0.97	1.92	26.23	39.73	24.50	15.64	10.66	7.99	1.99	0.38
35+ years	44.50	47.07	1.14	1.60	21.64	31.86	21.26	10.57	8.20	7.01	3.25	1.88

Source: Author's calculations (2024) based on KCHS (2021). Weighted data

The educational structure creates a stark divide in the labor market, separating those with compulsory education from those with higher qualifications. As seen in Table 7, low-educated individuals are predominantly confined to low-skilled operative and blue-collar jobs, while highly educated individuals have greater 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 in professional positions.

Table 7. Type of occupation in primary job: distribution by education and gender (%)

	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

[3] 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.

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

Source: Author's calculations (2024) based on KCHS-2021 data.

5.2.3 The unadjusted gender earnings difference

Table 8 presents the raw gender pay gap in Kenya's labor market, analyzed across earnings percentiles, age cohorts, and employment sectors. Among employees aged 15 to 65, women's average earnings are approximately 89.1% of men's earnings (=exp (8.746)/exp (8.861)). For workers aged 15-34, women earn 93.3% of men's earnings (=exp (8.597)/exp (8.666)), while for those aged 35 and above, women earn 85.7% of men's wages (=exp (8.908)/exp (9.062)). These results highlight significant differences in the unadjusted gender pay gap across age groups. Moreover, the unadjusted gender pay gap varies across the earnings distribution. Women's earnings reach nearly 90% of men's at the top quartile and 88% at the bottom quartile but drop to around 77% at the median quartile. This suggests that the raw earnings disparity between men and women are more pronounced at the median quartile but this narrows at the extremes of the earnings distribution. These findings align partially with studies by Kolev and Robles (2010) on Ethiopia.

Related to the above, the unadjusted gender earnings gap is slightly higher in the public sector compared to the private formal sector, though the difference is negligible. In the private formal sector, women's earnings represent 88.9% (=exp (9.572)/exp (9.689)) of men's earnings, while in the public sector, women earn 92% of men's earnings. In contrast, the raw gender earnings gap is wider in the informal sector, where women's earnings amount to only 71.9% (=exp (8.0982)/exp (8.427)) of men's earnings. Overall, these findings indicate that men enjoy a wage premium over women in both formal (public and private) and informal sectors. Additionally, earnings are higher in the public sector compared to the private formal sector, with men benefiting more than women.

Table 8: The unadjusted gender pay gap by age groups, percentiles, and employment sector.

Age cohorts (%)				Wage percentiles (%)			Employment sector (%)		
15+		15-34	35+	P25	P50	P75	Public	Private formal	Informal
89.1		93.3	85.7	87.5	76.2	89.7	92.0	88.9	71.9

Source: Author's calculations (2024) based on KCHS (2021). Note: Female earnings in terms of men earnings (Kenya shillings).

Furthermore, on average, both low-educated and highly educated women earn less than their male counterparts (Table 9). The raw earnings gap is 0.3538 log points for low-educated women and 0.1163 log points for highly educated women, indicating that the disparity is more pronounced among low-educated workers. However, the pattern of this gap varies across the earnings distribution by education level. For low-educated workers, the gap follows a U-shaped pattern: it is highest at the bottom of the distribution (0.5108 log points at the 10th percentile), lowest at the 25th percentile (0.2231 log points), and then rises again at the top (0.4855 log points at the 75th percentile). In contrast, for highly educated workers, the earnings gap increases across the distribution, peaking at the median (0.1823 log points at the 50th percentile) and declining slightly at the top (0.1744 log points at the 75th percentile). Altogether, among highly educated workers, the raw earnings gap is more pronounced in the middle and upper parts of the distribution, while for low-educated workers, it is most significant at the lower end.

Table 9: Raw gender earnings difference by educational attainment (in log points)

	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 (2024) based on KCHS-2021 data.

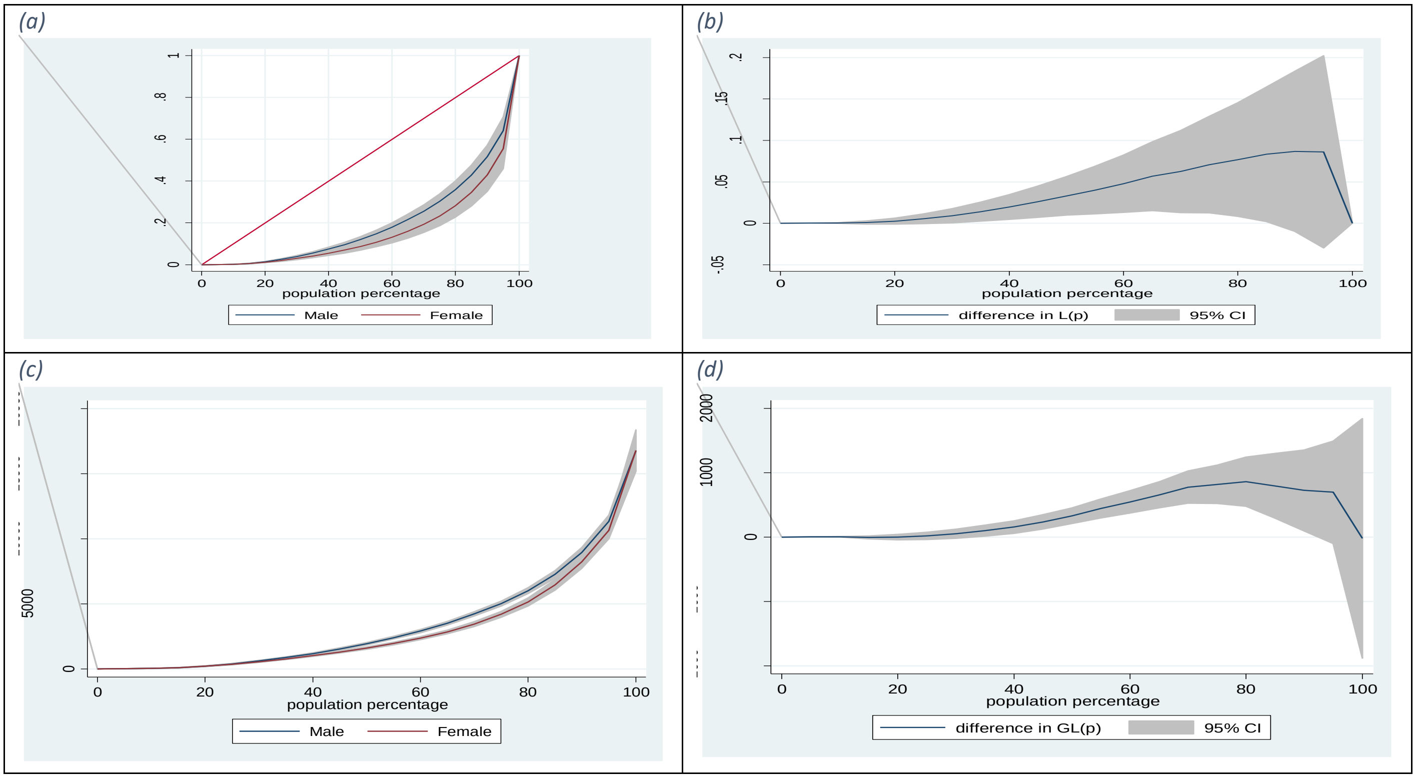
To comprehensively assess raw gender earnings disparities, it is essential to move beyond average income comparisons and analyze how earnings are distributed across the population distribution. Figure 8 shows Lorenz curves—which plot cumulative monthly earnings (vertical axis) against population percentiles (horizontal axis)—to illustrate these patterns. For wage-employed workers, the standard Lorenz curve for men (Figure 8a) consistently lies above that for women, revealing that women not only earn less on average but also face inequality between 40^{th}

and 90th percentiles of the population distribution. While the gender gap in cumulative earnings is minimal at the extremes of the distribution (i.e., the lowest and highest percentiles), it widens markedly as the population share increases, underscoring systemic disparities in income progression.

Figure 8(b) mirrors the trend in earnings difference observed in 8(a) showing how men's earnings distribution dominates the women's across the population distribution. At the lowest percentiles below (e.g., the poorest below 40th percentile), earnings disparities are negligible, suggesting parity in economic outcomes for men and women in the most disadvantaged population. Progressing to higher population shares—especially between the 40th and 90th percentiles—the divergence increases. The earnings difference rise more steeply, reflecting greater access to opportunities for men's income growth relative to women. This asymmetry underscores systemic barriers that disproportionately limit women's ability to attain higher earnings, even among top earners.

To evaluate welfare implications, generalized Lorenz curves—which account for both average income and distributional equity, offering holistic measure of economic welfare—are analyzed in figures 8(c) and 8(d). The generalized Lorenz curve addresses a limitation of the standard Lorenz curve: while the latter focuses solely on inequality (relative distribution), the former integrates both inequality *and* average income into a welfare metric. In other words, the generalized Lorenz curve multiplies the standard Lorenz curve by the mean income of the population. This adjustment allows us to assess welfare holistically—where a group (men) with higher average income and less inequality will have a generalized Lorenz curve that dominates (lies above) another (women). Figure 8(d) mirrors the trends in earnings difference observed in 8(c) showing how men's earnings distribution dominates the women's across the population distribution and welfare perspective. It's clear from figure 8(c) that men's generalized Lorenz curve dominates women's, indicating that men's earnings yield superior welfare outcomes. This signifies that the men's earnings distribution is not only less unequal but also more favorable from a welfare perspective, enjoying superior welfare outcomes. This dual advantage arises from the compounding effect of higher average earnings and a more favorable distribution. In contrast, the women's subdued curve reflects persistent economic disempowerment, as their earnings lag behind the men's even when welfare considerations are integrated. The sharp decline in the earnings difference after the 90th percentile across the population distribution may reflect women's career advancement in high-paying roles in sectors.

Figure 8: Lorenz curves and Generalized Lorenz dominance curves



Source: Author's calculations (2024) based on KCHS (2021). Note: Monthly earnings in Kenya shillings (Ksh.). The generalized curves account for the sampling weights.

5.2.4 Kernel density estimation of earnings

To comprehensively analyze earnings disparities between Kenya's formal (public and private) and informal sectors, Figure 9(a) presents a kernel density plot which tells us that public sector earnings are generally higher than those in both private formal and informal sectors. This is evident from the right-skewed curve, which also has a wider distribution of earnings in the public sector, reflecting greater variability. Public sector wages are regulated by standardized pay scales, such as gazetted minimum wages, and supported by collective bargaining agreements (315 agreements registered in 2022), ensuring wage stability. For example, the Teachers Service Commission (TSC) and county governments are major public employers, with TSC wages increasing by 3% in 2022. Moreover, public sector jobs are predominantly located in urban areas like Nairobi and Mombasa, where gazetted minimum wages are 12% higher than in rural areas, further boosting public sector earnings. In contrast, the informal sector's lower earnings are largely due to its reliance on informal employment, which accounted for 86.1% of new jobs in 2022. Informal jobs in sectors such as trade, manufacturing, and transport typically lack regulated wages. For instance, the average monthly wage in informal agriculture was KSh 10,107, significantly lower than public sector averages (e.g., KSh 842,872.8 annually in the public sector) (KNBS *Economic Survey*, 2023).

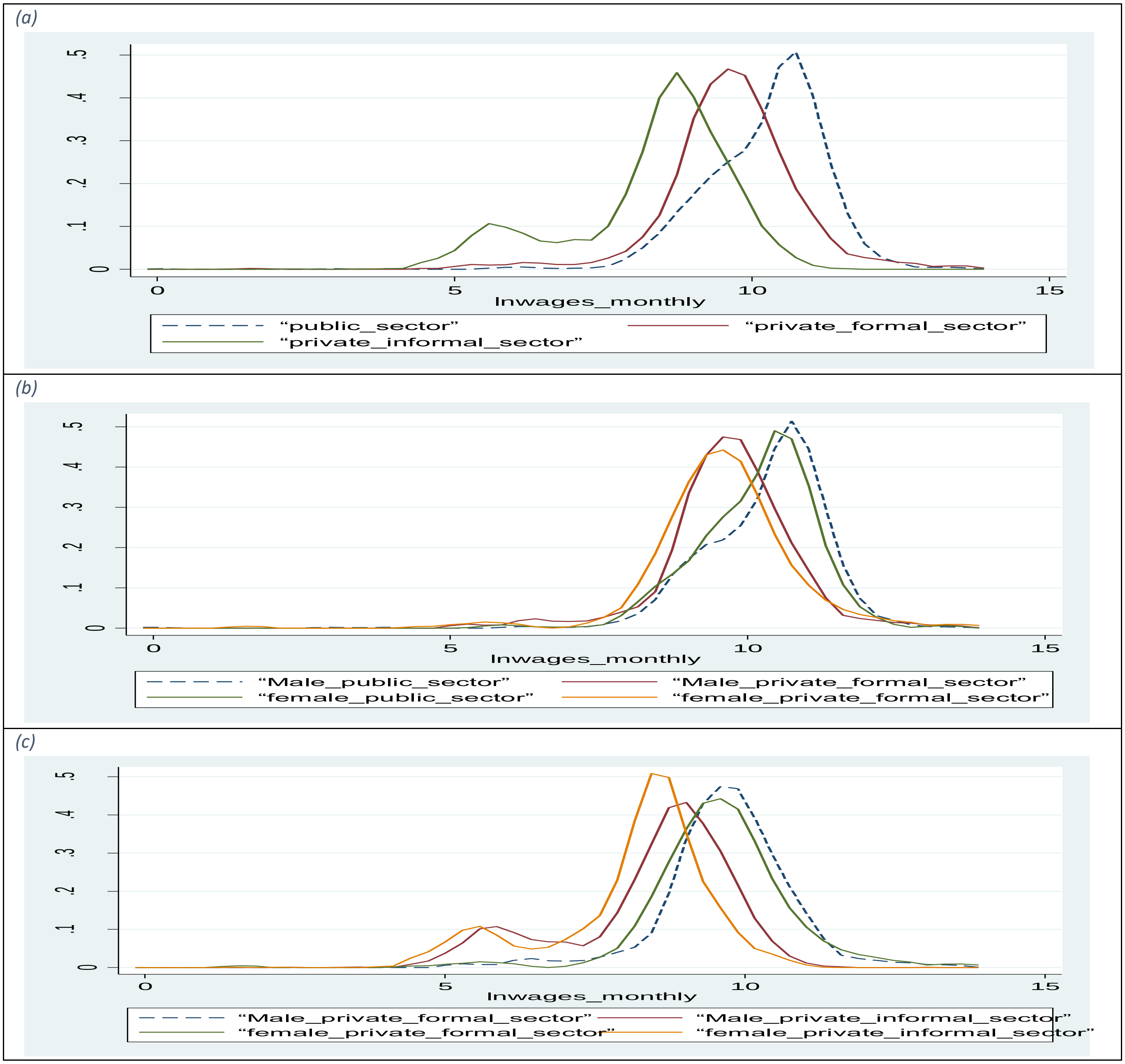
Figure 9(b) indicates that men generally earn slightly higher wages than women across the earnings distribution i.e., women face disadvantages across the entire earnings spectrum, suggesting the presence of a either a "sticky floor" or "glass ceiling" effect in Kenya's formal sector. This disparity can be attributed to sectoral and occupational biases. For instance, men dominate higher-paying industries such as mining (87.2% male), manufacturing (77.1% male), and transportation, while women are overrepresented in lower-paid sectors like household employers (66.2% female) and health/social work (53.4% female). Notably, the gap is slightly wider in the private formal sector and becomes more pronounced across the wage distribution, though it narrows in the upper tail (Figure 9c). These findings align with existing literature (Agesa et al., 2009; Agesa et al., 2013; Omanyo, 2021).

Table 10 reinforces the Kernel density visualizations, presenting the logarithm of earnings and the earnings gap across various quantiles and at the mean across employment sectors. The results tell us that male earnings consistently exceed female earnings across all quantiles and sectors, with the exception of the private formal sector, where women earn more at the 90th percentile. The mean raw gender earnings gap, calculated as the log of male earnings minus the log of female earnings, is largest in the informal sector (0.329 log points), followed by the public sector (0.142 log points), and smallest in the private formal sector (0.116 log points). The patterns of the pay gap vary by sector. In the public sector, the gap is widest at the 50th and 90th percentiles, narrowest at the 25th quartile, but remains significant even at the 10th percentile. In the private formal sector, the pay gap is largest at the lower end of the earnings distribution (10th percentile and 25th quartile), decreases sharply at the 50th percentile, and then rises again at the upper quartiles. In the informal sector, the gap is most pronounced at both the lower and upper quartiles of the earnings distribution.

The public sector's right-skewed earnings distribution reflects the prevalence of senior roles in education, health, and administration, which command higher pay brackets. For instance, public administration and defense alone accounted for 35.7% of public sector employment. In contrast, the private formal sector's narrowing gender gap at the 90th percentile may be attributed to an increasing representation of women in high-skilled roles, such as finance and IT. On the other hand, the informal sector's significant earnings gap at the lower end (0.288 log points) highlights the prevalence of low-paying, unregulated jobs in agriculture and trade. While Kenya's 2022 minimum wage increases and collective bargaining efforts have helped reduce disparities in the formal sectors, these measures have yet to reach the informal economy, leaving approximately 16 million workers vulnerable to low wages and poor working conditions.

Figure 10(a) confirms that earnings generally increase with age, with older workers earning more than younger workers in the upper tails of the earnings distribution, regardless of gender. However, in the median quartiles, younger workers tend to earn more, while at the lower end of the distribution, there are no significant differences in earnings across age groups. Focusing on youth (Figure 10b), the earnings gap is evident across the entire distribution, but it narrows in the upper tail. For workers aged 35 and above, Figure 10(b) confirms that earnings rise with age, with the gap significantly narrowing in the upper tail but remaining pronounced in the lower and middle quartiles.

Figure 9: Kernel density plot of earnings distribution by gender and employment sector.



Source: Author's calculations (2024) based on KCHS (2021). Note: Individuals aged 15-65 years. Monthly earnings in Kenya shillings (Ksh.).

Table 10: Log monthly earnings at different percentiles

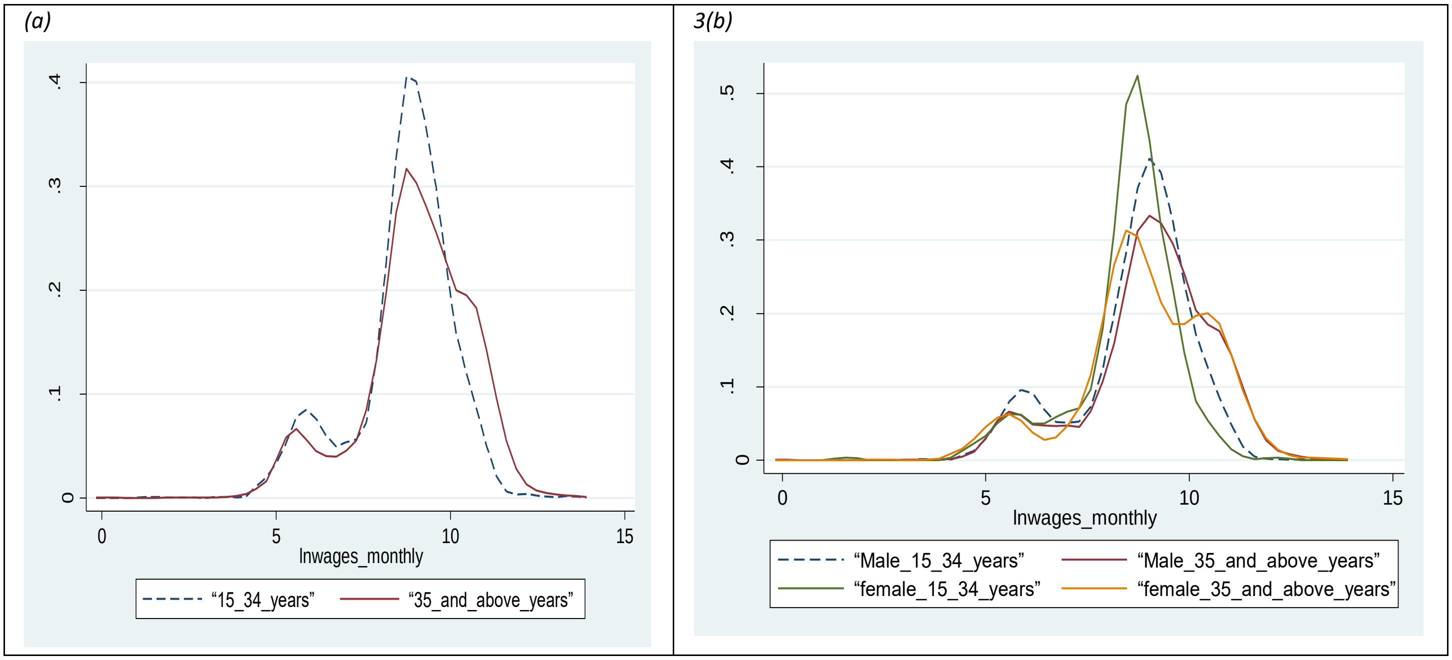
	Public sector			Private formal sector			Private informal sector		
Percentile	Men	Women	Gap	Men	Women	Gap	Men	Women	Gap
10^{th}	8.987	8.854	0.133	8.699	8.476	0.223	5.992	5.704	0.288
25^{th}	9.649	9.616	0.033	9.210	8.987	0.223	8.006	7.601	0.405
50^{th}	10.545	10.333	0.212	9.694	9.616	0.078	8.740	8.476	0.264
75^{th}	10.951	10.819	0.132	10.309	10.126	0.183	9.393	8.881	0.512
90^{th}	11.374	11.197	0.177	10.824	10.873	-0.049	9.893	9.457	0.436
Mean	10.297	10.155	0.142	9.689	9.573	0.116	8.427	8.098	0.329

Source: Author's calculations (2024) based on KCHS (2021).

The lower earnings for younger workers can be attributed to the dominance of Kenya's informal sector, which constitutes 81% of non-agricultural employment. This sector is characterized by low wages, instability, and a lack of regulated pay scales. Younger workers (15–34 years) often enter the labor market through informal roles, such as agriculture, retail, or gig work, where earnings are suppressed. Additionally, Kenya's youth unemployment rate reached 13% in 2022 with a 20% NEET rate (KLMP, 2024). Younger workers frequently face prolonged job searches or settle for casual jobs, which make up 17.1% of private sector employment, contributing to lower earnings at the lower end of the distribution. In contrast, the higher median quartile earnings for youth can be explained by the significant enrollment in TVET institutions, which rose to 643,000 students in 2023. Younger workers with vocational skills may secure slightly better-paying roles in sectors like manufacturing, construction, or IT, which accounts for their competitive median earnings. However, these roles often lack seniority benefits or union protections, limiting their long-term earning potential.

The upper tail of the earnings distribution is dominated by older workers, primarily due to their experience and senior roles in formal sectors such as public administration, education, and healthcare, which account for 35.7% of public sector employment. These roles are governed by collective bargaining agreements**,** covering 24% of formal workers, ensuring higher wages. Furthermore, public sector jobs are concentrated in urban areas like Nairobi and Mombasa, where gazetted minimum wages are 12% higher than in rural areas. Older workers in urban formal roles benefit from structured pay scales and CBAs, which further widen the upper-tail earnings gap. To sum up, the earnings disparities across age cohorts in Kenya reflect the structural dynamics of the labor market. Younger workers face challenges in the informal economy and underemployment, while older workers benefit from experience, senior roles, and unionized formal employment.

Figure 10: Kernel density plot of earnings distribution by gender and Age cohorts.

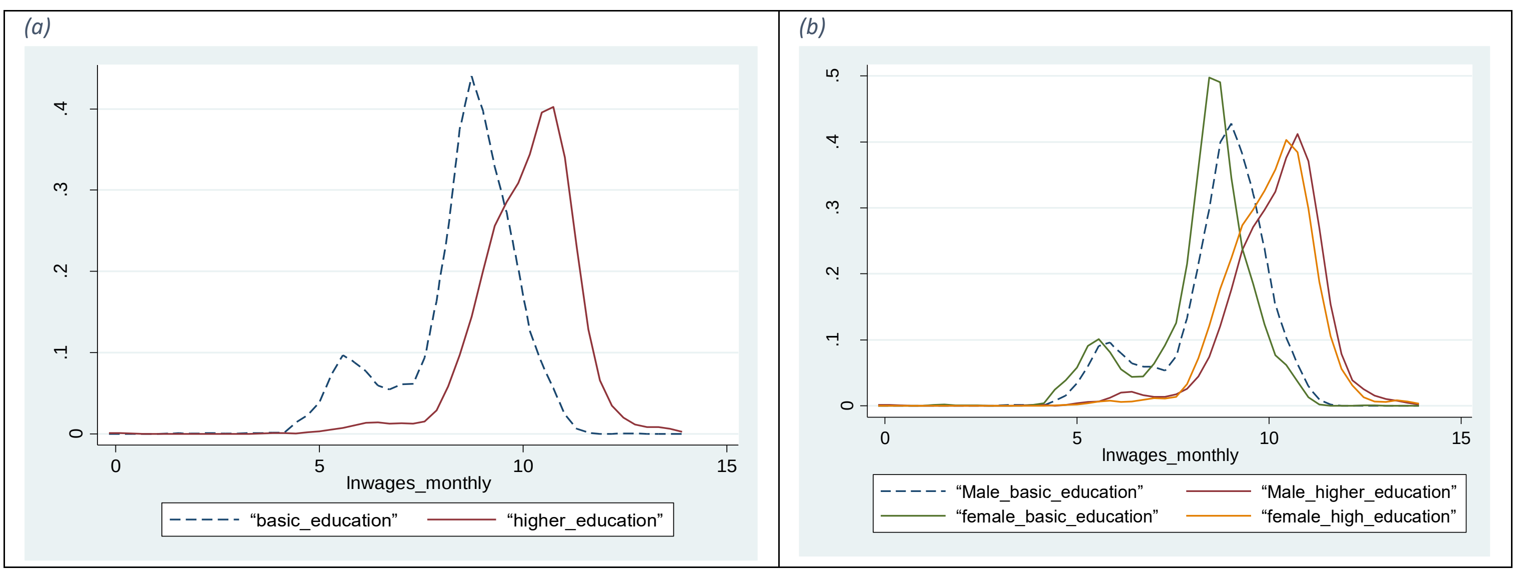


Source: Author's calculations (2024) based on KCHS (2021). Note: Monthly earnings in Kenya shillings (Ksh.).

Next, Figure 11 shows kernel density estimates of earnings distributions by gender and education level. The gap between the density curves for men and women reflects the raw gender earnings gap. In both low-educated and highly educated groups, earnings are skewed in favor of men, with a more pronounced disparity among low-educated workers. This is evident from the greater separation between male and female earnings density curves in the low-education group (Figure 11b). Highly educated workers generally earn more than their low-educated counterparts, as shown by the rightward skew in their earnings distribution (Figure 11a). In Figure 11a, the earnings distribution for highly educated workers shifts further right compared to low-educated workers for both genders. Also, earnings among highly educated workers are more dispersed, highlighting greater inequality within this group. Among highly educated workers, men still earn more than women across the earnings spectrum, though the gap narrows slightly at higher income levels (Figure 11b). Women, especially those with low education, face systemic barriers that trap them in low-wage jobs, creating a "sticky floor" effect in the earnings distribution.

Among low-educated workers[4], women's earnings are concentrated in the lower end of the distribution, indicating that a larger proportion of low-educated women are low-wage earners compared to men. The raw gender earnings gap persists through the median quartile, but it narrows significantly in the upper tail of the distribution. Even in low-paying jobs, men earn more than women, and low-educated men are more likely to achieve log earnings of 8.5 or higher. Overall, the raw gender earnings gap is more pronounced among low-educated workers, though it diminishes at higher income levels. While the earnings gap between highly educated men and women is narrower than for low-educated individuals, men still earn more than women across the earnings spectrum, particularly in the lower and middle ranges. This gap narrows slightly in the upper tail but persists throughout. These findings suggest a likely "sticky floor" effect in Kenya's labor market, where women, especially those with low education, face systemic barriers to advancing beyond low-wage jobs. The kernel density analysis reveals that a higher education alone does not eliminate gender disparities**.** Despite Kenya's strong legal framework for gender equality (scoring 84/100 on the Women, Business, and Law Index), cultural norms and unpaid care responsibilities disproportionately hinder women's labor market participation and wage progression.

Figure 11: Kernel density plot of earnings distribution by gender and education level.



Source: Author's calculations (2024) based on KCHS (2021). Note: Individuals aged 15 and 65 years. Monthly earnings in Kenya shillings (Ksh.).

[4] Here, low education means basic education which encompasses primary, post primary, and secondary.

5.3 Chapter conclusion

This chapter's descriptive analysis reveals persistent gender disparities in Kenya's labor market, shaped by structural inequities and socio-cultural norms. Key findings indicate that women face lower employment rates (73.56% vs. 80.40% for men), greater involvement in unpaid home labor (12.44% vs. 4.59%), and overrepresentation in the low-paying private informal sector (65.1% vs. 73.06% for men). Despite achieving higher educational attainment at advanced levels, women remain concentrated in lower-wage occupations and sectors, underscoring a paradox where education does not fully translate into equitable earnings. The unadjusted gender pay gap persists across all sectors and age cohorts, peaking in the informal sector (71.9% of men's earnings) and among older workers (85.7%).

The Lorenz curve analysis further highlights systemic inequality: while men's and women's earnings show near-parity at the lowest percentiles (1–15%), the gap widens sharply between the 15th and 95th percentiles. Men's cumulative earnings dominate women's across most of the distribution, reflecting disparities in income progression and opportunities for upward mobility. Generalized Lorenz curves, which integrate welfare considerations, confirm that men's economic outcomes are not only less unequal but also have superior overall welfare due to higher average earnings and a more favorable distribution. These patterns highlight entrenched barriers, such as occupational segregation and limited access to high-paying roles, that disproportionately constrain women's earnings trajectories.

Kernel density estimations further reinforce these findings, revealing systemic barriers where men's earnings dominate across distributions, with women—particularly low-educated ones—experiencing a likely "sticky floor" effect, trapped in low-wage roles and persistent gaps even among highly educated workers. Together, the evidence suggests that gender disparities permeate Kenya's labor market at every level—from employment composition and sectoral segregation to earnings distribution and welfare outcomes. These disparities are compounded by occupational segregation, limited access to formal employment, and cultural norms prioritizing men in high-paying sectors.

6. THE GENDER PAY GAPS IN KENYA'S FORMAL AND INFORMAL SECTORS AND ACROSS AGE COHORTS

This chapter moves to the empirical investigation of the first research objective: analyzing the gender pay gap in Kenya's formal (public and private) and informal sectors, as well as across distinct age cohorts. I advance two pivotal yet underexplored dimensions in existing literature. First, I examine the foundational determinants of earnings disparities between men and women, disaggregated by employment sector and age group. To address double selectivity bias—arising from non-random participation in employment and sectoral selection—I employ the Heckman two-step correction and the BFG models. Second, the gender pay gap is decomposed into composition effects and wage structural effects across the earnings distribution. This is achieved using the reweighted Oaxaca-RIF decomposition method. Here, I seek to provide a clear understanding of how sectoral dynamics and age-related labor market trajectories shape gender-based earnings inequities in Kenya.

6.1 Introduction

The persistence of gender disparities in labor market outcomes has been extensively documented in economic literature, with scholars highlighting systemic inequities in earnings, participation, and employment stability (World Bank, 2012). Modernization theory posits a positive correlation between economic development and female labor force participation, attributing this trend to labor demand growth and evolving societal norms that facilitate women's progressive integration into formal employment (Suh, 2017). However, despite these advancements, women continue to face persistent earnings gaps relative to men, alongside lower workforce participation rates and elevated unemployment levels. These enduring inequalities have driven scholarly attention to wage discrimination, especially since women's increased labor market entry has increased scrutiny of structural barriers perpetuating gendered disparities. Wage determination is shaped by a complex interplay of factors, including individual human capital attributes and structural market forces such as occupational segregation and institutional mechanisms like collective bargaining power and wage floor regulations (Hospido & Moral-Benito, 2016)

Analyses of the gender pay gap commonly decompose earnings disparities into two components: one attributable to differences in productivity-related characteristics and a residual, unexplained portion (e.g., Bertrand, 2020; Borrowman & Klasen, 2020). The latter is frequently interpreted as a measure of potential wage discrimination, reflecting systemic biases unaccounted for by observable factors (Firpo et al., 2009, 2018). A consistent conclusion across studies is that human capital, job attributes, and structural factors fail to fully explain the GPG, with the unexplained residual often comprising a substantial share of the disparity. Recent cross-sectoral analyses further reveal significant heterogeneity in the GPG's magnitude, both between public and private sectors, formal and informal sectors and across the earnings distribution spectrum (e.g., Campos et al., 2017; Castagnetti & Giorgetti, 2019; Holm-Hadulla et al., 2010; Mahuteau et al., 2017; San & Polat, 2012; Vilerts, 2018).

The observed variation in gender pay gaps between public/formal and private/informal sectors aligns with theoretical expectations, as these sectors operate under distinct institutional and market-driven wage-setting mechanisms. In the public sector, wage determination is embedded in political and regulatory frameworks, whereas private-sector wages are shaped by market forces and organizational discretion (Campos et al., 2017; Chassamboulli & Gomes, 2023; Dickson et al., 2014). This divergence in institutional contexts may explain why public-sector employment often yields relatively equitable wage outcomes for women. For instance, public-sector wage structures tend to emphasize standardized pay scales, transparency, and comparability, which can mitigate gender-based disparities (Pfeifer, 2008). Additionally, the public sector's stronger adherence to anti-discrimination legislation and higher unionization rates—with collective bargaining covering a larger share of workers—may further constrain discriminatory practices (Antonczyk et al., 2010; Card et al., 2020). Empirical evidence also suggests that occupational integration, such as the narrowing of gender representation gaps in higher-paying roles, has advanced more rapidly in public-sector employment compared to private-sector contexts.

Kenya's dualistic labor market structure—comprising a regulated formal sector (15.9% of employment) and a vast informal sector (84.1%)—exhibits divergent wage-setting mechanisms. The formal sector employs structured frameworks such as collective bargaining agreements and statutory minimum wages, while the informal sector remains unregulated, relying on market-driven negotiations. Notably, CBAs cover only 24% of formal wage employees (3.7% of total employment), with stark sectoral disparities: education and public administration account for 44% of covered workers, compared to 3.5% in manufacturing (KNBS *Economic Survey*, 2023). This imbalance reflects institutional gaps in enforcing labor rights, particularly in male-dominated industries like manufacturing, where unionization is fragmented.

The public sector, governed by administrative pay grades and the Salaries and Remuneration Commission, demonstrates marginally better gender parity in managerial roles (49.6% women in senior/middle management). However, overlapping mandates between the SRC and county governments create jurisdictional conflicts, undermining cohesive wage determination (KIPPRA, 2018). Conversely, the private sector ties wages to productivity and market dynamics, which often put women at a disadvantage due to occupational clustering in low-productivity roles (e.g., 66.2% of women in household employment). These sectoral dynamics justify the study's focus on comparing GPG trends across employment sectors, as structural inequities in wage governance and enforcement mechanisms likely exacerbate disparities in the informal sector.

Empirical evidence consistently documents a narrower gender pay gap in public-sector employment compared to private-sector roles (e.g., Arulampalam et al., 2007; Hyder & Reilly, 2005; Lausev, 2014; Ganguli & Terrell, 2005). Public-sector wage structures, shaped by bureaucratic transparency and pay comparability, often reduce scope for discretionary biases, yielding more equitable outcomes for women (Pfeifer, 2008; Antonczyk et al., 2010). However, this pattern is less evident in Sub-Saharan Africa, where systemic gender inequalities persist across sectors. In Kenya, for instance, men consistently out-earn women, though scholarly consensus on the drivers of this gap remains fragmented. Studies in Kenya (e.g., Agesa et al., 2013; Abdiaziz & Kiiru, 2021; Omanyo, 2021; UN women, 2023) debate whether the disparity stems primarily from *explained* factors or *unexplained* components, reflecting contextual complexities.

Notably, research in SSA, including Kenya, has predominantly analyzed GPG at the *conditional mean* level (*e.g.,* Kabubo-Mariara, 2003; Siphambe & Thokweng-Bakwena, 2001; Kolev & Robles, 2010; Kagundu & Pavlova, 2007), potentially overlooking distributional disparities. This contrasts with studies in advanced economies, which often employ quantile decomposition to reveal how gaps widen or narrow across wage percentiles (e.g., Arulampalam et al., 2007; Kee, 2006). The limited focus on distributional analysis in SSA contexts obscures the issue of whether gender disparities are concentrated among low-, middle-, or high-wage earners—a critical gap given the region's high informal employment and occupational segregation.

The examination of gender pay gaps across Kenya's unconditional earnings distribution remains underexplored, with only a handful of studies—notably Agesa et al. (2009, 2013) and Omanyo (2021)—employing distributional analyses to assess disparities at different wage percentiles. These studies, utilizing survey data from 2005/2006 and 2015/2016, respectively, confirm the persistence of a public-private sector wage dichotomy, where gender gaps in earnings systematically differ between public-sector roles and private-sector employment and in the labor market as a whole. However, the drivers of this divergence remain inadequately understood, highlighting critical gaps in contextual and institutional analysis.

This chapter advances the analysis of Kenya's gender pay gap by examining disparities across formal (public and private) and informal sectors, as well as age cohorts, while introducing critical methodological and contextual innovations to address gaps in existing literature. While building on foundational work, this study incorporates four underexplored dimensions of inquiry. First, it systematically evaluates the baseline determinants of earnings differentials between men and women, disaggregated by employment sector and age cohort. This dual stratification addresses a notable limitation in prior studies, failing to account for heterogeneity across demographic and institutional contexts. Second, the study rigorously addresses the issue of double-sample selectivity bias—a methodological challenge arising from the non-random selection of individuals into both employment and specific sectors (public, private formal, or informal). To mitigate this, I employ a triangulated econometric approach: the OLS regression to establish baseline associations, the Heckman two-step selection model to correct for non-random labor market participation, and the BFG model to simultaneously account for sectoral selection.

Unobserved factors influencing labor market participation and sectoral employment choices may significantly shape wage outcomes. Individuals possessing a comparative advantage in a specific sector often self-select into that sector, potentially yielding higher returns than those with similar observable traits but lacking such advantages. Correcting for this selectivity bias and endogeneity is essential, particularly in traditional Sub-Saharan African contexts where entrenched societal norms place women as subordinate and economically dependent on male spouses (Wanjala

& Were, 2009). These norms often relegate women to domestic roles while valorizing men's labor market participation, creating structural barriers that distort wage determinants.

Third, this study investigates gender pay gaps across Kenya's formal (public and private) and informal sectors, testing the hypothesis that wage discrimination diminishes in the public sector along the earnings distribution. Recognizing that sectoral choice is endogenously determined—shaped by unobserved preferences, comparative advantages, and structural constraints—I employ a dual methodological approach. At the conditional mean level, the standard Oaxaca-Blinder decomposition and its extensions are applied to disentangle gender disparities into *compositional effects* (attributable to differences in productive endowments) and *wage structure effects* (stemming from differential returns to these endowments). To extend this analysis across the *unconditional earnings distribution*, I utilize the reweighted RIF-Oaxaca decomposition. This approach quantifies the partial contribution of individual covariates to both compositional and structural effects, revealing which factors most significantly drive gender pay gaps at different wage percentiles.

Fourth, I investigate the gender pay gap across age cohorts, testing the hypothesis that the influence of human capital attributes on wage disparities varies significantly by age. To quantify these disparities across the *unconditional earnings distribution* within each cohort, I employ the reweighted RIF-Oaxaca decomposition. Kenya's pronounced youth bulge—with individuals aged 15–34 constituting 35% of the population and 80% under 35—presents both opportunities and challenges for equitable labor market outcomes. The country's demographic transition, marked by a declining age dependency ratio (69% in 2022), signals potential for a demographic dividend, yet systemic barriers persist, particularly for young women. Annual labor market entries exceed 800,000 youth, but only 15% secure stable employment, with most relegated to informal, low-wage roles lacking social protection (ILO, 2023). This structural mismatch is compounded by a 20% NEET rate (24% for women vs. 15% for men), reflecting gendered disparities exacerbated by caregiving responsibilities and cultural norms. Thus, analyzing GPG across age cohorts is critical to unravel how human capital elements differentially influence earnings over the life course. Younger cohorts, despite policy-driven gains in educational access, face overqualification in informal sectors and discrimination in male-dominated industries, while older workers contend with entrenched occupational segregation and motherhood penalties.

6.2 Literature Review

Research on gender pay disparities is extensive in advanced economies but remains nascent, though growing, across developing regions such as Asia, Latin America, and Sub-Saharan Africa. Existing studies confirm substantial gender pay gaps in multiple SSA nations, as evidenced by empirical analyses in Kenya (Agesa et al., 2013; Omanyo, 2021), Ghana (Danquah et al., 2021), Ethiopia (Temesgen, 2006; Kolev & Robles, 2010), and other contexts (Nordman et al., 2016; Kim, 2020; Midagbodji & Kouevidjin, 2020; Nkoumou & Wirba, 2021; Wirba et al., 2021; Gradín & Tarp, 2019). Recent scholarly works have increasingly focused on sectoral disparities, comparing public and private sectors, with a methodological shift toward analyzing how the GPG manifests across the earnings distribution—specifically at the lower, median, and upper segments.

Castagnetti and Giorgetti (2019) examined gender wage disparities in Italy's public and private sectors from 2005 to 2010, revealing a markedly higher gap in the private sector. After accounting for individual heterogeneity, their analysis showed a reduction in both the gender wage gap and wage curve steepness across sectors. Notably, the "sticky floor" effect—a concentration of wage disparities at lower earnings levels—observed in the private sector dissipated, while the public sector retained a persistent "glass ceiling" effect, reflecting barriers to women's advancement in higher-wage roles. Despite these differences, both sectors exhibited significant unexplained wage gaps, which were more pronounced in the public sector throughout the earnings distribution. In a parallel context, Azam and Prakash (2010) demonstrated that India's public sector consistently offered higher wages than the private sector for both genders, regardless of their position in the wage hierarchy, underscoring structural inequities in market-driven wage determination.

Barón and Cobb-Clark (2010) analyzed the gender pay gap across Australia's public and private sectors, examining disparities at all wage levels. Their findings revealed a critical divergence in the drivers of inequality: among high-wage workers, the GPG was primarily attributed to *unexplained factors* in both sectors. In contrast, for low-wage workers, the gap was largely *explained* by observable individual characteristics, such as education or experience. This pattern suggested that glass ceilings—systemic barriers limiting women's advancement to top-earning roles—were the dominant force behind wage inequities, rather than sticky floors, which denote entrenched disparities at the lower end of the wage distribution.

Arulampalam et al. (2007) conducted a cross-national analysis of sectoral gender pay gaps across eleven European countries, revealing that glass ceilings—systemic barriers limiting women's advancement to top earnings—were more pervasive than sticky floors in most contexts. Their findings underscored a significant variation in the GPG magnitude across the wage distributions of public and private sectors, with institutional and structural factors shaping divergent outcomes. In contrast, Kee (2006) observed a pronounced glass ceiling effect exclusively within Australia's private sector, highlighting sector-specific inequities in high-wage roles. Conversely, Wahlberg (2010) identified robust glass ceiling dynamics in *both* Sweden's public and private sectors, with the public sector exhibiting particularly stark disparities at upper wage tiers.

Rahona-López et al. (2016) documented persistent gender pay disparities in Spain, with significantly larger gaps in the private sector across all wage levels. Their analysis revealed a paradoxical dynamic in human capital distribution: women exhibited superior educational and skill endowments in the public sector, while men held comparable advantages in the private sector. Crucially, the GPG was most pronounced at the upper tiers of the earnings distribution, where differences in *returns* to human capital—rather than disparities in productive characteristics—explained over 80% of the wage gap among top earners.

Kim (2020) analyzed gender earnings disparities among young workers in Malawi using microdata from the School-to-Work Transition Survey, demonstrating that women's hourly wages constituted 80.6% of men's earnings. Applying the Oaxaca decomposition method, the study found that differences in labor market endowments—such as education and experience—explained the majority of monthly earnings gaps. However, a substantial proportion of the disparity stemmed from the *unexplained component*, indicative of discriminatory practices in wage determination. Notably, the research demonstrated that adopting a non-discriminatory wage structure would reduce overall earnings inequality by 7%, while equalizing educational attainment between genders could narrow the wage gap by 3–3.6%.

Kolev and Robles (2010) investigated gender wage disparities in Ethiopia using 2005 Labor Force Survey data from the Central Statistics Agency and found that women's earnings represented 66% of men's wages, highlighting substantial gender-based earnings inequality. The disparities were most acute among younger female workers, though the gap narrowed progressively with age. The study emphasized that the unexplained wage gap attributable to discrimination was more pronounced in the formal private sector compared to public-sector roles. Also, differences in educational attainment between genders explained a considerable share of earnings gaps across the labor market. However, among younger workers, educational factors played a diminished role in observed disparities, suggesting that structural inequities—such as occupational segregation or biased hiring practices—disproportionately affect early-career women.

Midagbodji and Kouevidjin (2020) investigated gender wage disparities in Togo's informal sector using data taken from the *Integrated Regional Survey on Employment and Information Sector*. Their analysis revealed significant earnings gaps, with men earning a wage premium of 1.081 log points over women on average. These disparities decreased progressively across the income distribution, ranging from 1.274 log points at the lower end to 0.754 log points at the higher end. The study attributed the gap primarily to productivity-related differences in human capital endowments, such as skills or experience. However, discriminatory practices disproportionately affected lower- and middle-income tiers, where structural inequities in wage-setting were most pronounced. Notably, the unexplained portion of the gap—interpreted as potential discrimination—peaked at the upper end of the distribution, accounting for 1.166% of the total discrepancy. While educational attainment exacerbated wage inequality across most income levels, its impact diminished in the highest quantile, suggesting that informal sector dynamics uniquely mediate returns to education.

Research on gender pay disparities across Kenya's employment sectors remains sparse. KIPPRA (2013) compared wage differentials between the public and private sectors, revealing that public sector workers generally received higher overall wages. However, when examining basic salaries specifically, the private sector exhibited higher wage premiums. Despite these insights, the study did not explicitly analyze gender dimensions within these disparities. In contrast, Kabubo-Mariara (2003) conducted a decomposition of the GPG between Kenya's public and private sectors, identifying systemic biases favoring men, though no direct discrimination against women was detected. The analysis further highlighted a more pronounced GPG in the private sector compared to the public sector, underscoring structural inequities in market-driven wage determination.

Agesa et al. (2013) applied RIF regressions to analyze the gender pay gap across Kenya's earnings distribution. Their findings revealed distinct drivers of inequality at different wage levels: at the lower end of the distribution, both compositional disparities and structural inequities exacerbated the GPG. Conversely, at the upper end, compositional differences—particularly in industry, occupation, higher education, and regional disparities—were the primary contributors to the widening gap. In the middle of the wage distribution, human capital factors exerted the strongest influence on the GPG's magnitude. The study highlighted how sectoral and occupational segregation, coupled with uneven returns to educational attainment, systematically disadvantage women across the earnings spectrum, with structural barriers disproportionately affecting lower-wage workers and compositional inequities intensifying disparities among higher earners.

Omanyo (2021) employed RIF regressions and data from the *2015/16 Kenya Integrated Household Budget Survey* to analyze gender wage disparities across Kenya's public and private sectors. The study identified systemic discrimination against women in both sectors, though it was less pronounced in the public sector. Even after accounting for observable characteristics, women consistently earned less than their male counterparts. The wage gap exhibited variability across the earnings distribution, narrowing between sectors at higher wage levels. Notably, a "sticky-floor" effect was observed in the public sector. And while the endowment effect favored women in the public sector, it gave men a strong advantage in both formal and informal private sectors.

6.3 Methods: RIF-Oaxaca decomposition.

The standard method for analyzing wage differences, introduced by Blinder (1973) and Oaxaca (1973), seeks to decompose average wage gaps between two groups. This approach assumes a linear wage-setting model that separates observable and unobservable characteristics. Over the past decade, various techniques have extended the Blinder-Oaxaca (1973) decomposition to analyze wage gaps across the entire distribution. While these methods are useful for breaking down wage differences into components explained by productivity characteristics and unexplained factors, most fail to identify the specific contribution of each independent variable. Fortin et al. (2011) addressed this limitation by proposing a technique that decomposes wage gaps for any distribution statistic, allowing the estimation of each variable's contribution to both the explained and unexplained parts of the wage gap across the income distribution.

Here, I employ the RIF quantile regression method formalized by Firpo et al. (2009, 2018). A RIF-regression is similar to a standard regression, except that the dependent variable, Y, is replaced by the (recentered) influence function of the statistic of interest. Consider IF(y, v), the influence function corresponding to an observed wage y for the distributional statistic of interest, $v(FY)$. The recentered influence function (RIF) is defined as RIF$(y; v) = v(FY) + IF(y; v)$, so that it aggregates back to the statistics of interest $RIF(y; v). \partial F(y) = v(FY) + IF(y; v)$. In its simplest form, the approach assumes that the conditional expectation of the $RIF(Y; v)$ can be modeled as a linear function of the explanatory variables,

$$\mathbb{E}\text{ RIF } (\text{Y}; v)|X = X\gamma, \tag{6.1}$$

where the parameters γ can be estimated by OLS. At the core of RIF regressions is the ability to generate the average effects of all explanatory variables at a particular earnings quantile. This is done by replacing the original dependent variable (log of monthly earnings) with the RIF.

$$RIF(W;\ q_\tau) =\ q_\tau + \frac{\tau - I(W \leq q_\tau)}{f_w(q_\tau)}\,, \tag{6.2}$$

where f_w is the marginal density function of earnings W and $I(W \leq q_\tau)$ is an indicator function. According to Firpo et al., (2009, 2018), if the RIF regression $E[RIF(W; q_\tau)|X]$ is well modeled by the linear regression model $E[RIF(W; q_\tau)|X] = X\beta$, then the estimated coefficients represent the mean marginal effects of explanatory variables on the earnings quantiles. Since the true $RIF(W;\ q_\tau)$ is unobservable, we shall use its sample analogue $RIF(W;\ \hat{q}_\tau)$ by replacing the unknown quantities with their corresponding estimators:

$$\widehat{RIF}(W; \hat{q}_\tau) =\ \hat{q}_\tau + \frac{\tau - I(W; \leq \hat{q}_\tau)}{\hat{f}_w(\hat{q}_\tau)}\,, \qquad (6.3).$$

where $\hat{q}_\tau$ is the τth sample quantile and $\hat{f}_w$ is the kernel density estimator. Firpo et al. (2009) showed that the coefficient estimates $\hat{\beta}$ generated from RIF regressions provided the average effect of the explanatory variables on earnings.

The RIF regression is a function $E[RIF(Y; v)|X = x]$, where v represents the distributional statistic of interest. By taking iterated expectations, the derived marginal effects of the covariates on the statistic of interest are obtained by averaging the RIF function with respect to changes in the distribution of the covariates. Like OLS regressions, RIF regressions typically assume a linear specification $E[RIF(Y;\hat{q}_\tau)|X] = X\beta$, where the coefficient β represents the marginal effect of X on the distributional statistic-in this case the quantile $\hat{q}_\tau$. The empirical estimation of RIF regressions involves two steps. The first step is a reweighting procedure, where three weighting functions (ω) are estimated:

$$\widehat{\omega}_m M = \frac{1}{\hat{p}} \tag{6.4}$$

$$\widehat{\omega}_f F = \frac{1}{(1-\hat{p})} \tag{6.5}$$

$$\widehat{\omega}_c C = \frac{1}{P} * \frac{\hat{p}\,(x)}{1-\hat{p}(x)}\,, \tag{6.6}$$

where $\widehat{\omega}_m M$ is the weight for the distribution of male workers, $\widehat{\omega}_f F$ is the weight for the distribution of female workers, and $\widehat{\omega}_c C$ is the female counterfactual weighting function that would prevail if female workers had the same distribution of observed and unobserved characteristics as males.

The variable x is the distribution of covariates and $\hat{p}$ is the probability that an individual i is male. The coefficient $\hat{p}(x) = p_r(m|x)$ is the propensity score, i.e., the conditional probability that individual i is male, given a set of observed covariates x. The propensity score is important because the data may be vulnerable to endogeneity, i.e., omitted variable bias correlated with unmeasured aspects of finding work for male workers. The propensity score helps to adjust for this potential endogeneity.

In the second step, I estimate RIF unconditional quantile wage regressions for male, female, and counterfactual female earnings, which can be expressed as:

$$\widehat{RIF}(\omega_k;\hat{q}_\tau) = X_k\hat{\beta}_k\,, \tag{6.7}$$

where $k = m, f, c$ and $\widehat{RIF}(\omega_k;\hat{q}_\tau)$ is the RIF estimate at the τ^{th} quantile $\hat{q}$. The coefficient $\hat{\beta}$ is the estimate of the unconditional quantile partial effect. Using the unconditional quantile regression estimates from Equation (7), if $v(W)$ is a quantile of the earnings distribution W (in logarithmic), we can get the male–female pay gap $\left[v(W)_m - v(W)_f\right]$ at selected quantiles and decompose the pay gap into portions attributable to differences in characteristics (composition effects) and the return to characteristics (wage structure effects).

The decomposition is generalized as follows:

$$\left[v(W)_m - v(W)_f\right] = \left[v(W)_m - v(W)_c\right] + \left[v(W)_c - v(W)_f\right], \quad (6.8).$$

where the first component on the right−hand side $[v(W)_m - v(W)_c]$ represents the composition effects, i.e., the gender earnings difference due to differences in productivity-related endowments weighted by the coefficients attributable to male individuals i.e., male wage structure as non-discriminatory[5]. The second term on the right−hand side $\left[v(W)_c - v(W)_f\right]$ represents the wage structure effect, i.e., the gender earnings differences due to differences in the returns to productivity-related characteristics between men and women.

The aggregate structural effect obtained by reweighting can be further broken down into a RIF structural effect and a RIF reweighting error (Gang et al., 2021). Similarly, the composition effect can be decomposed into a RIF composition effect and a specification error. The linear nature of the RIF regressions allows us to get the contribution of each explanatory variable to each of these four components and the detailed structural effect and composition effect.

Next, the overall decomposition can be expressed as:

$$\hat{q}_\tau(W_m) - \hat{q}_\tau(W_f) = \{\bar{X}_f(\hat{\beta}_c - \hat{\beta}_f) + \hat{R}_\tau^S\} + \{\overline{(X}_m\hat{\beta}_m - \bar{X}_f\hat{\beta}_f) + \hat{R}_\tau^c\}, \quad (6.9).$$

where $\hat{q}_\tau(W_m) - \hat{q}_\tau(W_f)$ represents the raw gender wage differential at the τth quantile, while $\bar{X}_f$ and $\bar{X}_m$ represent the vector of average covariates for female and male workers, respectively. The coefficient $\hat{\beta}_c$ is the estimate from the counterfactual distribution, which assumes the female distribution that would prevail if female workers had the same distribution of observed and unobserved characteristics as males. The gap $(\hat{\beta}_c - \hat{\beta}_f)$ measures the male and female differences in returns to productivity-related characteristics, and the magnitude $\bar{X}_f(\hat{\beta}_c - \hat{\beta}_f)$ represents the wage structure effect, i.e., the gender wage differential at the τth quantile

[5] It should be mentioned that the decomposition in Equation (8) is performed using the coefficients from the sample of males as the reference category. However, the choice of reference category can significantly affect the decomposition results, leading to what is known as the 'index number problem' in the literature (Oaxaca 1973). The literature suggested using the average of male and female coefficients as the reference (Cotton 1988; Neumark 1988; Reimers 1983). The standard practice in the literature on the gender wage gap is to use the male coefficients as the non-discriminatory wage structure.

attributable to different returns in the productivity-related characteristics for male and female workers. The difference $\overline{(X_m}\hat{\beta}_m - \bar{X}_f\hat{\beta}_f)$ represents the composition effect, i.e., the gender wage differential at the τth quantile attributable to gender differences in the labor market characteristics. The magnitudes $\hat{R}_\tau^S$ and $\hat{R}_\tau^c$ are the estimates of the approximation errors corresponding to the wage structure and composition effects, respectively (Firpo et al., 2009), specified as follows:

$$\hat{R}_\tau^s = \left[(q)(W_c) - \hat{q}\left(W_f\right)\right] - \left[\overline{X_f}\left(\hat{\beta}_c - \hat{\beta}_f\right)\right] \qquad (6.10).$$

And

$$\hat{R}_\tau^c = [\hat{q}(W_m) - \hat{q}(W_c)] - \left[\bar{X}_m\hat{\beta}_m - \bar{X}_f\hat{\beta}_c\right] \qquad (6.11).$$

The $\hat{\beta}_f$ and $\hat{\beta}_m$ are the estimated coefficients obtained from unconditional quantile regression for female and male workers. The coefficient $\hat{\beta}_c$ is derived from unconditional regression estimates based on the counterfactual earnings of female workers. In other words, $\hat{\beta}_c$ assumes that the returns to the distribution of earnings for female workers are just as if they possessed the same distribution of observable and unobservable characteristics as male workers. Since these counterfactual earnings assume that male returns to the labor market characteristics also apply to women, the coefficient $\hat{\beta}_c$ can be compared with $\hat{\beta}_m$. Moreover, the specific estimates for $\hat{\beta}_c$ are also reported in the results.

Regarding wage structure effects, if the return to a variable X is higher for males compared to females ($\hat{\beta}_c > \hat{\beta}_f$), it indicates a positive wage structure effect, suggesting potential discrimination or bias against women. Conversely, if the return to variable X is higher for females compared to males ($\hat{\beta}_f > \hat{\beta}_c$), it leads to a negative wage structure effect. When the explanatory variable is a dummy variable, the estimate tells us the contribution of that specific dummy variable relative to the designated base group. In terms of composition effects, $\overline{(X_m}\hat{\beta}_m - \bar{X}_f\hat{\beta}_c)$, since $\hat{\beta}_c$ is comparable to $\hat{\beta}_m$, the composition effect associated with variable X captures the wage gap attributed to gender differences in X (endowments), assuming the same returns for both men and women.

6.4 Empirical Results and Discussion

6.4.1 Mean characteristics by employment sector and age cohorts

Table 11 presents demographic and employment characteristics of male and female workers in Kenya's formal (public and private) and informal sectors, revealing notable gender disparities. Sectoral distribution shows 15% of men work in the public sector, 10% in the private formal sector, and 73% in the informal sector. For women, 23% are in the public sector, 11% in the private formal sector, and 65% in the informal sector. Interestingly, men outnumber women in each sector. Female workers are generally younger and less likely to be married than their male counterparts, with the public sector having a higher proportion of married employees. Educationally, women, on average, tend to have higher qualifications, particularly in the public and private formal sectors, where more women hold diplomas, bachelor's, and postgraduate degrees. Despite this, men earn higher wages, with an average log wage of 8.861 compared to 8.746[6] for women. This gap persists across both sectors, with public sector earnings being higher than private sector earnings for both genders.

The data also highlights gender differences in working hours and rural-urban employment distribution. On average, men work more hours per week in their primary occupation than women across all sectors. In rural areas, more men are employed in the public sector, while in urban areas, women outnumber men across all sectors. Women are predominantly concentrated in elementary occupations, agriculture, forestry, fishery, and service or trade-related roles in both the private formal and informal sectors. In contrast, men dominate the public sector across all occupational categories. These findings indicate that despite women’s slightly higher educational attainment, significant gender disparities persist in the labor market, particularly in sectoral distribution, working hours, and occupational concentration.

[6] Using the *SVY* specification to account for complex survey estimation in our data, the total population size = 5,390,236, with the male population size = 3,446,776 while the women subpopulation size = 1,943,46. With this specification, log average male earnings = 9.0264 while the women’s log earnings = 8.932, resulting in a gender gap of 0.094 log points or 9.9%.

Table 11: Mean characteristics of variables by gender and employment sector.

	Men				Women			
	All	Public sector	Private formal	Informal sector	All	Public sector	Private formal	Informal sector
Sector of employment		15.84	10.88	73.28		23.00	11.83	65.17
Log earnings	8.861 (1.503)	10.295 (1.091)	9.689 (1.0766)	8.427 (1.384)	8.746 (1.546)	10.155 (0.987)	9.572 (1.236)	8.0982 (1.342)
Age	35.979 (11.181)	41.562 (10.220)	35.221 (9.655)	34.88 (11.234)	35.107 (10.559)	38.996 (10.201)	31.840 (8.699)	34.327 (10.623)
Household size	4.205 (2.494)	4.239 (2.365)	3.486 (2.134)	4.303 (2.553)	4.392 (2.332)	4.233 (2.063)	3.719 (2.203)	4.570 (2.418)
Firm size	3.852 (1.934)	5.5007 (1.698)	5.692 (1.492)	3.222 (1.632)	3.805 (2.010)	5.343 (1.561)	5.595 (1.398)	2.937 (1.678)
Tenure	7.222 (7.714)	11.692 (9.384)	6.807 (6.358)	6.31637 (7.144)	7.194 (7.941)	11.119 (9.753)	5.0519 (5.0573)	6.1984 (7.165)
Hours of work (weekly)	50.634 (17.716)	48.953 (15.483)	53.786 (16.812)	50.529 (18.237)	43.698 (16.0725)	42.176 (8.856)	50.0346 (14.579)	43.0856 (17.940)
Residence								
Rural	0.580 (0.493)	0.514 (0.5001)	0.305 (0.461)	0.635 (0.481)	0.535 (0.498)	0.471 (0.499)	0.269 (0.444)	0.606 (0.488)
Urban	0.419 (0.493)	0.485 (0.5001)	0.694 (0.461)	0.364 (0.481)	0.464 (0.498)	0.528 (0.499)	0.730 (0.444)	0.393 (0.488)
Marital status								
Married	0.676 (0.467)	0.889 (0.314)	0.766 (0.423)	0.616 (0.486)	0.554 (0.497)	0.7562 (0.429)	0.487 (0.5007)	0.494 (0.5001)
Cohabiting	0.00404 (0.0634)	0.00449 (0.0669)	0.00436 (0.066)	0.00388 (0.0622)	0.00409 (0.0638)	0.00177 (0.0421)	0.01038 (0.101)	0.00376 (0.0612)
Separated	0.0688 (0.253)	0.0299 (0.171)	0.0502 (0.218)	0.08006 (0.271)	0.176 (0.381)	0.0871 (0.282)	0.131 (0.338)	0.216 (0.412)
Single	0.251 (0.433)	0.0764 (0.265)	0.179 (0.383)	0.299 (0.457)	0.264 (0.441)	0.154 (0.362)	0.3702 (0.483)	0.284 (0.451)
Education								
Primary	0.455 (0.498)	0.109 (0.312)	0.218 (0.413)	0.565 (0.495)	0.425 (0.494)	0.0498 (0.217)	0.1384 (0.345)	0.609 (0.487)
Post-primary	0.0225 (0.148)	0.0164 (0.127)	0.0109 (0.104)	0.0256 (0.157)	0.0114 (0.106)	0.00711 (0.0841)	0.0242 (0.154)	0.0106 (0.102)
Secondary	0.336 (0.472)	0.254 (0.436)	0.395 (0.489)	0.344 (0.475)	0.269 (0.443)	0.145 (0.353)	0.276 (0.448)	0.312 (0.463)
Diploma	0.115 (0.319)	0.316 (0.465)	0.248 (0.432)	0.0525 (0.223)	0.2103 (0.407)	0.530 (0.499)	0.415 (0.493)	0.0603 (0.238)
Bachelors	0.0612 (0.239)	0.262 (0.440)	0.104 (0.306)	0.0113 (0.105)	0.0708 (0.256)	0.227 (0.419)	0.121 (0.326)	0.00628 (0.079)
Post-graduate	0.00902 (0.0945)	0.0404 (0.197)	0.0218 (0.146)	0.000324 (0.0180)	0.0122 (0.110)	0.0391 (0.194)	0.0242 (0.154)	0.000628 (0.0250)
Occupation								
Occ1	0.0199 (0.139)	0.109 (0.312)	0.00655 (0.0807)	0.00259 (0.0508)	0.0188 (0.135)	0.0676 (0.251)	0.0103 (0.101)	0.00314 (0.0559)
Occ2	0.107 (0.3102)	0.490 (0.5002)	0.165 (0.372)	0.0165 (0.127)	0.209 (0.406)	0.693 (0.461)	0.3217 (0.467)	0.0175 (0.131)
Occ3	0.0425 (0.201)	0.1034 (0.304)	0.0829 (0.276)	0.0233 (0.151)	0.0257 (0.158)	0.0427 (0.202)	0.0692 (0.254)	0.0119 (0.108)
Occ4	0.00641 (0.0798)	0.0254 (0.157)	0.0131 (0.113)	0.00129 (0.0359)	0.0253 (0.157)	0.0747 (0.263)	0.0553 (0.229)	0.00251 (0.050)

Occ5	0.144 (0.351)	0.158 (0.365)	0.307 (0.462)	0.117 (0.321)	0.178 (0.382)	0.0711 (0.257)	0.332 (0.471)	0.188 (0.391)
Occ6	0.208 (0.406)	0.0194 (0.138)	0.0698 (0.255)	0.270 (0.444)	0.275 (0.446)	0.0124 (0.111)	0.0830 (0.276)	0.402 (0.491)
Occ7	0.211 (0.408)	0.0254 (0.157)	0.137 (0.344)	0.262 (0.439)	0.0372 (0.189)	0.0231 (0.150)	0.0381 (0.191)	0.0420 (0.2008)
Occ8	0.130 (0.337)	0.0419 (0.2006)	0.174 (0.380)	0.143 (0.350)	0.0163 (0.126)	0.00355 (0.0596)	0.0415 (0.199)	0.0163 (0.126)
Occ9	0.128 (0.334)	0.0254 (0.157)	0.0414 (0.199)	0.163 (0.369)	0.213 (0.409)	0.0106 (0.102)	0.0484 (0.215)	0.315 (0.464)
Employment contract								
Written Agreement	0.339 (0.473)	0.794 (0.404)	0.654 (0.476)	0.136 (0.343)	0.400 (0.490)	0.785 (0.410)	0.694 (0.461)	0.121 (0.327)
Verbal Agreement	0.383 (0.486)	0.0653 (0.247)	0.203 (0.403)	0.518 (0.499)	0.3404 (0.473)	0.0647 (0.246)	0.198 (0.399)	0.521 (0.499)
Implied contract	0.0417 (0.200)	0.0592 (0.236)	0.0450 (0.207)	0.0357 (0.185)	0.0360 (0.186)	0.0431 (0.203)	0.0257 (0.158)	0.0349 (0.183)
No contract	0.234 (0.423)	0.0805 (0.272)	0.0971 (0.296)	0.309 (0.462)	0.223 (0.416)	0.106 (0.308)	0.0808 (0.273)	0.321 (0.467)
Industry of work								
Primary sector	0.284 (0.451)	0.0374 (0.1900)	0.104 (0.306)	0.364 (0.481)	0.339 (0.473)	0.0177 (0.132)	0.121 (0.326)	0.493 (0.500)
Manufacturing	0.0482 (0.214)	0.0209 (0.143)	0.128 (0.335)	0.0421 (0.200)	0.0241 (0.153)	0.0142 (0.118)	0.0553 (0.229)	0.0219 (0.146)
Mining/extractives	0.0251 (0.156)	0.00299 (0.0547)	0.0196 (0.138)	0.0307 (0.172)	0.00368 (0.0605)	-	-	0.0056 (0.0749)
Tertiary sector 1	0.192 (0.394)	0.0419 (0.2006)	0.0764 (0.265)	0.242 (0.428)	0.0122 (0.110)	0.00889 (0.0939)	0.00692 (0.0830)	0.0144 (0.119)
Tertiary sector 2	0.0707 (0.256)	0.00749 (0.0863)	0.168 (0.374)	0.0700 (0.255)	0.113 (0.317)	0.00711 (0.0841)	0.214 (0.411)	0.132 (0.339)
Tertiary sector 3	0.137 (0.343)	0.0464 (0.210)	0.209 (0.407)	0.145 (0.353)	0.0225 (0.148)	0.00889 (0.093)	0.0968 (0.296)	0.0138 (0.116)
Tertiary sector 4	0.0885 (0.284)	0.289 (0.453)	0.106 (0.309)	0.0424 (0.201)	0.0728 (0.259)	0.167 (0.373)	0.110 (0.314)	0.0326 (0.177)
Tertiary sector 5	0.134 (0.341)	0.551 (0.497)	0.183 (0.387)	0.0376 (0.190)	0.303 (0.459)	0.772 (0.419)	0.384 (0.487)	0.123 (0.328)
Tertiary sector 6	0.0180 (0.133)	0.00149 (0.0387)	0.00218 (0.0467)	0.0239 (0.153)	0.108 (0.310)	0.00355 (0.0596)	0.0103 (0.101)	0.162 (0.369)
Religion								
Christianity	0.856 (0.350)	0.898 (0.302)	0.866 (0.340)	0.845 (0.361)	0.940 (0.236)	0.927 (0.260)	0.958 (0.199)	0.942 (0.233)
Islamic	0.0731 (0.260)	0.0794 (0.270)	0.0961 (0.295)	0.0683 (0.252)	0.0384 (0.192)	0.0533 (0.224)	0.0276 (0.164)	0.0351 (0.184)
Other religions	0.0705 (0.256)	0.0224 (0.148)	0.0371 (0.189)	0.0858 (0.280)	0.0208 (0.142)	0.0195 (0.138)	0.0138 (0.117)	0.0226 (0.148)
Union membership	0.0757 (0.264)	0.325 (0.468)	0.1004 (0.300)	0.0181 (0.133)	0.0982 (0.297)	0.354 (0.478)	0.0795 (0.271)	0.0113 (0.105)
N	4,210	667	458	3,085	2,443	562	289	1,592

Source: Author's calculations (2024) based on KCHS (2021). Note: Standard deviation in brackets. Note: Occ1- Legislatures, Administrators & Managers; Occ2- Professionals; Occ3- Technicians and associate professionals; Occ4- Clerical works; Occ5- Service workers, shop, and market sales; Occ6- Skilled agriculture, fishery, & forestry; Occ7- craft and trade related works; Occ8- Plant and machine operators and assemblers; Occ9- Elementary Occupations.

6.4.2 Baseline determinants of male-female earnings

I shall assess OLS log earnings functions using a set of explanatory variables to compare the impact of various factors on earnings across genders. To address the double-selection bias, I first generate selectivity correction terms for labor force participation and for sectoral employment choice. The analysis begins with the full sample of wage employment, followed by age cohorts (15-34 years and 35+ years), applying Heckman's two-step procedure to correct for labor force participation bias. I then evaluate log earnings functions for sectors—public, private formal, and informal—using the BFG procedure to correct for sectoral choice bias.

The conventional Mincer earnings equation includes human capital variables which influence earnings. Since actual labor market experience is unavailable in the KCHS 2021 data, potential experience—calculated as age minus years of schooling minus six pre-school years (Age-S-6)—is used as a proxy. Kenya's 8-4-4 education system comprises eight years of primary, four years of secondary, and four years of university education (Muricho & Chang'ach, 2013). Thus, 12 years of schooling are used to compute potential experience. However, this measure may overestimate experience for women, as their labor market participation is often interrupted by childcare and domestic responsibilities (Omanyo, 2021; Agesa et al., 2013; Robles & Kolev, 2010).

Two specifications are used in the earnings equation estimation. The first is an augmented Mincer wage equation, incorporating job characteristics such as employment sector, tenure, hours worked, occupation, industry, firm size, and employment contracts, alongside human capital attributes and other observable factors like marital status, residence, union membership, and religion. The second follows the traditional Mincer approach, excluding job characteristics. The first specification may underestimate the effect of education on earnings, as job characteristics, partly influenced by education, absorb some of its impact. However, including job characteristics is increasingly seen as essential, as they significantly determine earnings and contribute to the gender pay gap (Kolev & Robles, 2010). Consequently, the subsequent estimations will include both human capital endowments and job-related characteristics.

To account for selectivity-bias, I applied the Heckman and BFG modes. The estimation process involves two stages. In the first stage, I estimated the maximum likelihood estimates of probit/multinomial logit models separately calculated for men and women to model the probability of labor force participation in wage employment (the selection equation). The selection variables included age age-squared, household size, household head, married, urban locality, education. Here, household size was the exclusion restriction (proxy for number of children in the household). From the first stage, I generated the selectivity-bias correction terms—the inverse of Mills ration—which was then included in the wage regression, assuming joint normality of the error terms in the selection and wage equations, allowing the inverse Mills ratio to appropriately adjust for selection bias.

The selection correction terms (Heckman's inverse Mills ratio and BFG estimates) are statistically significant in most wage equations, indicating sensitivity to selection bias (tables 12–14). This underscores the importance of the exclusion restriction variables—household size and household head status—which influence labor force participation and sectoral choice but are excluded from the earnings equation itself. These variables act as instruments, ensuring identification by affecting selection into employment/sectors without directly determining wages, a critical assumption in Heckman/BFG methodologies. The effects are particularly pronounced for male workers in the informal sector and across age cohorts, aligning with findings by Danquah et al. (2021), Agesa et al. (2013), Omanyo (2021), Robles and Kolev (2010), and Kabubo-Mariara (2003). After controlling for observable characteristics and selection bias, a significant gender earnings penalty persists, evidenced by the negative coefficient of the female dummy variable (Table 8). Women earn approximately 81.1% of men's wages ($exp\ (-0.173) - 1$), associated with 18.9% penalty (full sample). This aligns with studies in Kenya (Omanyo, 2021; Agesa et al., 2013; Kabubo-Mariara, 2003; Abdiaziz & Kiiru, 2021), South Africa (Kwenda & Ntuli, 2018), and Nigeria (Aderemi & Alley, 2019).

Table 12: OLS and Heckman Selectivity corrected Log earnings by gender (Full sample)

	All		Men		Women	
	OLS	Heckman	OLS	Heckman	OLS	Heckman
Female	-0.160***	-0.173***	-		-	
	(0.0343)	(0.0346)				
Potential experience	0.0304***	0.0266***	0.0230***	0.0179***	0.0392***	0.0374***
	(0.00485)	(0.00504)	(0.00636)	(0.00670)	(0.00768)	(0.00783)
Potential experience square	-0.000554***	-0.000442***	-0.000405**	-0.000253	-0.000762***	-0.000708***
	(0.000131)	(0.000137)	(0.000166)	(0.000178)	(0.000219)	(0.000223)
Married	-0.0263	0.0451	0.0854*	0.174***	-0.128***	-0.0828
	(0.0335)	(0.0428)	(0.0475)	(0.0603)	(0.0484)	(0.0611)
Household size	-0.0347***	-0.0412***	-0.0406***	-0.0482***	-0.0265***	-0.0312***
	(0.00622)	(0.00667)	(0.00789)	(0.00850)	(0.0102)	(0.0109)
Urban	0.168***	0.151***	0.114***	0.0923**	0.240***	0.229***
	(0.0338)	(0.0344)	(0.0436)	(0.0445)	(0.0536)	(0.0543)
Christian	0.201***	0.203***	0.234***	0.237***	0.140	0.143
	(0.0656)	(0.0656)	(0.0738)	(0.0737)	(0.157)	(0.157)
Islamic	0.501***	0.503***	0.555***	0.557***	0.424**	0.428**

	(0.0875)	(0.0875)	(0.101)	(0.101)	(0.195)	(0.195)
Firm size	0.107***	0.109***	0.110***	0.112***	0.0983***	0.0987***
	(0.00939)	(0.00940)	(0.0120)	(0.0120)	(0.0153)	(0.0153)
Hours of work	0.00880***	0.00863***	0.00790***	0.00769***	0.0105***	0.0104***
	(0.000914)	(0.000916)	(0.00115)	(0.00116)	(0.00156)	(0.00156)
tenure	0.0118**	0.0120**	0.0146*	0.0146*	0.00632	0.00657
	(0.00579)	(0.00579)	(0.00748)	(0.00748)	(0.00914)	(0.00914)
Tenure square	-0.000203	-0.000212	-0.000330	-0.000334	3.13e-05	2.29e-05
	(0.000183)	(0.000183)	(0.000240)	(0.000240)	(0.000284)	(0.000284)
Primary	-0.233**	-0.236**	-0.166	-0.169	-0.457**	-0.458**
	(0.108)	(0.108)	(0.127)	(0.127)	(0.214)	(0.214)
Secondary	0.0725	0.0750	0.0985	0.101	-0.0732	-0.0687
	(0.109)	(0.109)	(0.128)	(0.128)	(0.214)	(0.214)
Diploma	0.493***	0.410***	0.517***	0.408***	0.343	0.296
	(0.116)	(0.120)	(0.140)	(0.147)	(0.218)	(0.222)
Bachelors	0.949***	0.867***	0.927***	0.819***	0.822***	0.778***
	(0.126)	(0.129)	(0.153)	(0.160)	(0.232)	(0.235)
Postgraduate	1.639***	1.556***	1.696***	1.583***	1.382***	1.338***
	(0.183)	(0.186)	(0.240)	(0.244)	(0.299)	(0.301)
Public sector	0.630***	0.626***	0.621***	0.615***	0.701***	0.700***
	(0.0665)	(0.0665)	(0.0857)	(0.0857)	(0.107)	(0.107)
Private formal	0.400***	0.398***	0.393***	0.387***	0.403***	0.404***
	(0.0572)	(0.0572)	(0.0726)	(0.0726)	(0.0942)	(0.0942)
Occ1	0.329**	0.341***	0.384**	0.397**	0.277	0.287
	(0.129)	(0.129)	(0.167)	(0.167)	(0.203)	(0.203)
Occ2	0.147*	0.158*	0.419***	0.427***	-0.166	-0.158
	(0.0844)	(0.0845)	(0.116)	(0.116)	(0.126)	(0.126)
Occ3	0.331***	0.343***	0.453***	0.465***	0.114	0.124
	(0.0953)	(0.0954)	(0.117)	(0.117)	(0.172)	(0.172)
Occ4	0.178	0.193	0.301	0.313	-0.0330	-0.0233
	(0.142)	(0.142)	(0.248)	(0.248)	(0.179)	(0.179)
Occ5	-0.0603	-0.0480	0.0684	0.0813	-0.238**	-0.230**
	(0.0667)	(0.0668)	(0.0932)	(0.0933)	(0.0952)	(0.0954)
Occ6	-0.278***	-0.273***	-0.141*	-0.136*	-0.462***	-0.458***
	(0.0587)	(0.0587)	(0.0750)	(0.0750)	(0.0958)	(0.0959)
Occ7	0.0205	0.0240	0.0924	0.0956	0.0374	0.0381
	(0.0757)	(0.0757)	(0.0902)	(0.0902)	(0.155)	(0.155)
Occ8	-0.0254	-0.0176	0.115	0.123	-0.0317	-0.0263
	(0.0837)	(0.0837)	(0.0984)	(0.0984)	(0.217)	(0.217)
Unionization	0.275***	0.275***	0.204**	0.204**	0.373***	0.372***
	(0.0597)	(0.0596)	(0.0796)	(0.0795)	(0.0890)	(0.0890)
Primary sector	-0.280**	-0.283**	-0.197	-0.202	-0.572	-0.572
	(0.131)	(0.131)	(0.145)	(0.145)	(0.424)	(0.424)
Manufacturing	-0.0302	-0.0284	-0.0267	-0.0232	-0.226	-0.225
	(0.135)	(0.135)	(0.149)	(0.149)	(0.426)	(0.426)
tertiary_sector1	-0.145	-0.142	-0.0619	-0.0574	-0.530	-0.536
	(0.129)	(0.129)	(0.138)	(0.138)	(0.461)	(0.461)
tertiary_sector2	-0.0954	-0.0974	-0.0517	-0.0510	-0.402	-0.404
	(0.134)	(0.134)	(0.154)	(0.154)	(0.422)	(0.422)
tertiary_sector3	-0.108	-0.106	-0.113	-0.110	0.0756	0.0764
	(0.120)	(0.120)	(0.129)	(0.129)	(0.434)	(0.434)
tertiary_sector4	-0.0205	-0.0213	0.0189	0.0213	-0.318	-0.321
	(0.0826)	(0.136)	(0.154)	(0.154)	(0.425)	(0.425)
tertiary_sector5	-0.139	-0.140	-0.186	-0.181	-0.370	-0.373
	(0.131)	(0.131)	(0.151)	(0.151)	(0.418)	(0.418)
tertiary_sector6	0.0996	0.0807	0.273	0.247	-0.351	-0.360
	(0.142)	(0.142)	(0.192)	(0.192)	(0.424)	(0.424)
Written contract	0.186**	0.767***	0.717***	-0.0213	0.8129***	0.763***
	(0.0940)	(0.0493)	(0.0638)	(0.0693)	(0.0750)	(0.0493)
Inverse Mills Ratio	-	-0.268***	-	-0.336**	-	-0.169
		(0.0997)		(0.141)		(0.139)
Constant	7.694***	8.015***	7.368***	7.756***	7.926***	8.108***
	(0.190)	(0.224)	(0.213)	(0.268)	(0.499)	(0.520)
Observations	6,653	6,653	4,210	4,210	2,443	2,443
R-squared	0.412	0.412	0.366	0.367	0.499	0.499

Source: Author's calculations (2024) based on KCHS (2021). Note: Individuals aged 15 and above. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Note: the dependent variable is the logarithm of monthly earnings. Note: Selection variables in the Heckman model includes Age, Age2, married, education, household head, household size, and urban residence. Note: Occ1- Legislatures, Administrators & Managers; Occ2- Professionals; Occ3- Technicians and associate professionals; Occ4- Clerical work; Occ5- Service workers, shop, and market sales; Occ6- Skilled agriculture, fishery, & forestry; Occ7- craft and trade related works; Occ8- Plant and machine operators and assemblers. Note: Post-primary education is the reference category for education levels while Occ9: elementary occupations is the reference category for occupations.

The selectivity-corrected models (Heckman and BFG) show that most coefficients change marginally, but their signs remain consistent with OLS results, so I interpret the OLS findings. Returns to education by gender are significant across all wage equations (full sample, sectors, and age cohorts), with higher returns at higher education levels, aligning with human capital theory (Mincer, 1974). Primary education (with post-primary as reference category) is negatively associated with earnings for both genders, particularly in the public sector, private formal sector, and full sample. However, postgraduate education is positively associated with earnings for women in the private formal sector and younger women (15–34 years) compared to those aged 35+.

In the public sector, men tend to be associated with slightly higher returns to postgraduate education compared to women. However, the higher premiums for women in other sectors can be attributed to a "catching up" effect, driven by improved gender equality in access to technical education (e.g., TVET) in Kenya, which has enhanced women's human capital and earning potential. Also, women have increasingly entered traditionally male-dominated occupations (e.g., professionals, technicians, managers) and industries[7] (e.g., finance, transport, public administration), spurred by shifts in consumer demand and technological advancements. These changes have enabled women to command higher wages in these expanding job markets.

The results (Table 13) indicate that for male workers, having a postgraduate education is associated with a 203%[8] increase in earnings in the public sector and 442% increase in the private formal sector, while for women, a postgraduate education is associated with a 129% increase in the public sector. On average, returns to education are higher in the private formal sector than in the public sector, with the association being stronger among women. In contrast, the association is

[7] The service industry is disaggregated into six sectors: tertiary sector 1 (electricity, gas and water supply, construction), tertiary sector 2 (wholesale and retail trade, hotels and restaurants), tertiary sector 3 (transport, storage and communications, financial intermediation), tertiary sector 4 (real estate, renting and business activities, public administration, compulsory social security), tertiary sector 5 (education, health and social work, other community, social and personal service activities) and tertiary sector 6 (private households with employed persons).

[8] The percentage figure is calculated as $(e^{1.109} - 1) \times 100$.

relatively lower and statistically insignificant in the informal sector, most likely due to limited demand for highly educated individuals. For younger workers, postgraduate education is strongly associated with earnings for women than for men. However, among older workers, men benefit more from higher education than women. These findings partially align with Kolev and Robles (2010), who found that education is more rewarded in private wage employment, particularly in Ethiopia's informal private sector. In Kenya, the results are consistent with Kabubo-Mariara (2003), Omanyo (2021), Agesa et al. (2013), and Kagundu and Pavlova (2007) for Uganda. However, they contrast with Kuepie et al. (2009), who observed higher returns to education in the public sector across West African cities.

Potential work experience has a positive and concave association with earnings for both men and women, with slightly higher returns for women in the public and informal sectors. However, in the private formal sector, the association is insignificant for both genders. Younger workers (15–34 years), particularly men, face challenges due to prior experience requirements, which significantly associated their earnings. Similarly, tenure—years spent in the current primary occupation—has a significant and concave association with earnings, more pronounced on women in the public and private formal sectors. These findings align with existing literature (Kolev & Robles, 2010; Kagundu & Pavlov, 2007; Agesa et al., 2013; Kwenda & Ntuli, 2018; Aderemi & Alley, 2019).

Union membership (e.g., COTU and Federation of Kenya Employers) is associated with an earnings premium, particularly for women in the full sample, public sector, private formal sector, and among older workers. However, the association is insignificant in the informal sector and only significant for male workers in the private formal sector. Among younger workers (15–34 years), the union premium is evident only for women. The lack of significance in the informal sector may stem from wages being determined through direct employer-employee contracts rather than collective bargaining, as seen in the public sector (Bhorat et al., 2002). These results are consistent with studies by Ntuli (2007) and Omanyo (2021), which also highlight the positive effect of union membership on wages.

Table 13: OLS and Selectivity Corrected (BFG method) Log earnings equations by gender and employment sector.

	Public sector				Private formal sector				Informal sector			
	Men		Women		Men		Women		Men		Women	
	OLS	BFG	OLS	BFG	OLS	BFG	OLS	BFG	OLS	BFG	OLS	BFG
Potential experience	0.0311*	-0.0385	0.0425***	-0.103	0.000193	-0.00303	-0.000390	0.00866	0.0266***	0.0107	0.0409***	0.0415***
	(0.0169)	(0.0720)	(0.0154)	(0.150)	(0.0175)	(0.0569)	(0.0219)	(0.0605)	(0.00748)	(0.0140)	(0.00976)	(0.0155)
Square of experience	-0.000519	0.000296	-0.00872**	0.00151	0.000310	8.96e-05	0.000480	0.000479	-0.00552***	-0.000398	-0.00889***	-0.00876**
	(0.000392)	(0.00103)	(0.000402)	(0.00240)	(0.000484)	(0.00142)	(0.000681)	(0.00190)	(0.000199)	(0.000293)	(0.000281)	(0.000380)
Married	0.0830	-0.462	-0.0288	-0.474	0.216*	0.385	-0.0554	0.0228	0.0651	-0.158	-0.174***	-0.145
	(0.125)	(0.511)	(0.0788)	(1.550)	(0.117)	(1.156)	(0.131)	(0.484)	(0.0562)	(0.185)	(0.0639)	(0.198)
Household size	-0.0295*	-0.0339	-0.0227	-0.0418	-0.00866	-0.0465	-0.0123	-0.00587	-0.0447***	-0.0332**	-0.0329**	-0.0353
	(0.0167)	(0.0363)	(0.0167)	(0.0660)	(0.0216)	(0.187)	(0.0290)	(0.0900)	(0.00949)	(0.0165)	(0.0134)	(0.0230)
Urban	0.124	0.197	0.184**	0.494	0.159	0.713	0.233	0.0554	0.121**	-0.0716	0.241***	0.243
	(0.0799)	(0.332)	(0.0720)	(0.848)	(0.103)	(1.595)	(0.153)	(1.032)	(0.0550)	(0.187)	(0.0764)	(0.303)
Christian	-0.0367	-0.0279	-0.382	-0.405	-0.109	-0.150	0.0267	0.0778	0.271***	0.277***	0.277	0.280
	(0.244)	(0.265)	(0.238)	(0.727)	(0.229)	(0.451)	(0.502)	(1.187)	(0.0836)	(0.102)	(0.207)	(0.303)
Islamic	0.100	0.0814	-0.0435	-0.516	0.177	0.140	-0.671	-0.424	0.618***	0.633***	0.624**	0.605*
	(0.272)	(0.292)	(0.274)	(0.822)	(0.264)	(0.477)	(0.622)	(1.531)	(0.121)	(0.129)	(0.265)	(0.336)
Firm size	0.0362	0.0282	0.0644***	0.0447	0.0557*	0.0451	0.0112	0.0202	0.124***	0.123***	0.123***	0.122***
	(0.0229)	(0.0328)	(0.0236)	(0.0562)	(0.0312)	(0.0656)	(0.0481)	(0.0845)	(0.0150)	(0.0144)	(0.0207)	(0.0215)
Hours of work	-0.00458*	-0.00458	0.00837**	0.00932	-0.00482*	-0.00490	0.00340	0.00242	0.0115***	0.0111***	0.0111***	0.0107***
	(0.00252)	(0.00290)	(0.00384)	(0.0101)	(0.00281)	(0.00490)	(0.00466)	(0.00625)	(0.00140)	(0.00170)	(0.00190)	(0.00221)
Tenure	0.0191	0.0239	0.0275*	0.0919*	0.0507**	0.0484	0.101***	0.0962	0.0131	0.0137	-0.00853	-0.00594
	(0.0157)	(0.0189)	(0.0151)	(0.0499)	(0.0208)	(0.0380)	(0.0293)	(0.0716)	(0.00925)	(0.00940)	(0.0121)	(0.0145)
Tenure square	7.14e-05	-7.87e-05	-0.000299	-0.00187	-0.00116	-0.00111	-0.0313***	-0.00300	-0.000581*	-0.00590*	0.000277	0.000204
	(0.000426)	(0.000470)	(0.000413)	(0.00128)	(0.000748)	(0.00148)	(0.00102)	(0.00323)	(0.000309)	(0.000323)	(0.000397)	(0.000481)
Primary	-0.731**	-0.712**	-0.932**	-1.073*	-0.566	-0.638	-0.927**	-0.865*	-0.0883	-0.0778	-0.362	-0.361*
	(0.300)	(0.278)	(0.411)	(0.636)	(0.421)	(0.600)	(0.411)	(0.513)	(0.148)	(0.161)	(0.299)	(0.196)
Secondary	-0.249	-0.266	-0.197	-0.385	-0.240	-0.264	-0.219	-0.153	0.149	0.150	-0.0461	-0.0543
	(0.291)	(0.287)	(0.392)	(0.587)	(0.419)	(0.565)	(0.390)	(0.420)	(0.150)	(0.154)	(0.300)	(0.183)
Diploma	0.219	-1.911	0.207	1.084	0.182	0.574	0.206	0.00691	0.507***	-0.712	0.228	-0.340
	(0.295)	(1.946)	(0.386)	(3.010)	(0.427)	(2.517)	(0.396)	(3.284)	(0.178)	(0.900)	(0.322)	(2.010)
Bachelors	0.529*	-1.598	0.606	1.390	0.782*	1.150	1.007**	0.803	0.807***	-0.413	0.831*	0.465
	(0.297)	(1.915)	(0.392)	(3.040)	(0.441)	(2.772)	(0.432)	(3.072)	(0.263)	(0.840)	(0.489)	(1.629)
Postgraduate	1.109***	-1.028	0.830*	1.393	1.690***	1.952	2.595***	2.404	2.091	0.898	0.480	0.161
	(0.342)	(1.535)	(0.423)	(3.042)	(0.513)	(2.092)	(0.551)	(3.115)	(1.314)	(0.744)	(1.251)	(0.556)
Occ1	0.727***	0.597	0.730**	0.732	-0.0213	0.137	1.054	1.059	0.325	0.379	0.555	0.321
	(0.268)	(0.383)	(0.358)	(0.929)	(0.592)	(0.609)	(0.656)	(0.823)	(0.468)	(0.286)	(0.564)	(0.542)
Occ2	0.819***	0.763**	0.352	0.423	0.548**	0.585*	0.0594	0.220	0.675***	0.657***	-0.209	-0.237
	(0.260)	(0.320)	(0.335)	(0.921)	(0.272)	(0.348)	(0.345)	(0.622)	(0.208)	(0.129)	(0.258)	(0.292)
Occ3	0.848***	0.831***	0.673*	0.488	0.781***	0.896*	0.512	0.617	0.297*	0.300*	-0.0638	-0.0122
	(0.274)	(0.296)	(0.361)	(0.965)	(0.291)	(0.490)	(0.388)	(0.633)	(0.171)	(0.165)	(0.308)	(0.347)
Occ4	0.544	0.521	0.416	0.294	0.635	0.575	0.227	0.407	0.383	0.348	-0.354	-0.289
	(0.332)	(0.395)	(0.353)	(0.918)	(0.446)	(0.580)	(0.384)	(0.698)	(0.647)	(0.578)	(0.625)	(0.483)
Occ5	0.669***	0.621**	0.414	0.321	0.489*	0.523	0.00804	0.135	-0.112	-0.0976	-0.257**	-0.246**
	(0.256)	(0.271)	(0.347)	(0.826)	(0.264)	(0.398)	(0.316)	(0.521)	(0.117)	(0.133)	(0.116)	(0.125)
Occ6	0.474	0.362	-0.324	0.245	0.210	0.299	0.111	0.320	-0.147*	-0.132	-0.462***	-0.450***
	(0.365)	(0.541)	(0.461)	(0.955)	(0.276)	(0.306)	(0.384)	(0.413)	(0.0836)	(0.0831)	(0.111)	(0.128)
Occ7	0.664*	0.676**	0.424	0.388	0.220	0.308	0.456	0.551	0.116	0.122	0.0236	0.0488
	(0.344)	(0.296)	(0.403)	(0.906)	(0.279)	(0.374)	(0.463)	(0.650)	(0.105)	(0.120)	(0.203)	(0.213)
Occ8	0.554*	0.527	0.674	0.442	0.252	0.339	0.0185	0.102	0.161	0.161	0.0869	0.120
	(0.330)	(0.322)	(0.646)	(0.946)	(0.269)	(0.398)	(0.423)	(0.539)	(0.119)	(0.134)	(0.310)	(0.340)
Unionization	0.239***	0.228**	0.428***	0.387*	0.295**	0.306*	0.0997	0.131	-0.175	-0.199	-0.180	-0.220
	(0.0823)	(0.116)	(0.0754)	(0.205)	(0.149)	(0.172)	(0.234)	(0.314)	(0.176)	(0.229)	(0.294)	(0.396)
Primary sector	-0.401	-0.533	0.770	0.964	0.0494	0.0962	0.154	0.170	-0.134	-0.153	-0.442	-0.418
	(0.693)	(0.560)	(0.626)	(0.763)	(0.373)	(0.538)	(0.844)	(1.171)	(0.168)	(0.166)	(0.502)	(0.572)
Manufacturing	-0.444	-0.640	0.800	1.019	0.104	0.0741	0.144	0.355	-0.00819	-0.00496	-0.113	-0.0647
	(0.712)	(0.467)	(0.618)	(0.737)	(0.333)	(0.491)	(0.795)	(1.203)	(0.179)	(0.203)	(0.512)	(0.562)
tertiary sector1	-0.345	-0.504	0.130	0.477	0.0227	-0.0383	-	0	-0.0490	-0.0500	-0.392	-0.436
	(0.688)	(0.473)	(0.657)	(0.837)	(0.365)	(0.525)		(0.599)	(0.159)	(0.162)	(0.551)	(0.609)

tertiary_sector2	-0.238	-0.404	0.224	0.976	-0.222	-0.169	-0.0902	0.115	0.117	0.0946	-0.229	-0.205
	(0.779)	(0.490)	(0.673)	(0.671)	(0.347)	(0.569)	(0.795)	(1.136)	(0.184)	(0.169)	(0.502)	(0.562)
tertiary_sector3	-0.148	-0.294	0.726	1.071	0.104	0.0586	0.247	0.407	-0.201	-0.191	0.211	0.239
	(0.694)	(0.494)	(0.658)	(0.675)	(0.320)	(0.533)	(0.814)	(1.116)	(0.148)	(0.170)	(0.529)	(0.549)
tertiary_sector4	-0.266	-0.354	0.621	0.933	-0.331	-0.328	0.266	0.426	0.177	0.163	-0.343	-0.329
	(0.669)	(0.496)	(0.560)	(0.731)	(0.355)	(0.563)	(0.800)	(1.108)	(0.197)	(0.197)	(0.519)	(0.601)
tertiary_sector5	-0.729	-0.873*	0.461	0.679	-0.336	-0.310	-0.0534	0.0994	0.147	0.148	-0.157	-0.139
	(0.669)	(0.496)	(0.550)	(0.742)	(0.342)	(0.582)	(0.802)	(1.148)	(0.196)	(0.193)	(0.497)	(0.546)
tertiary_sector6	0.430	0.00599	-	0	-0.570	-0.591	0.256	0.494	0.315	0.314	-0.236	-0.214
	(1.134)	(0.417)		(0.751)	(0.976)	(0.551)	(0.973)	(1.062)	(0.213)	(0.197)	(0.501)	(0.565)
Constant	9.342***	14.38***	7.973***	9.198	8.847***	6.127	8.568***	9.376**	7.072***	7.012***	7.642***	7.734***
	(0.790)	(3.722)	(0.772)	(7.035)	(0.652)	(6.966)	(1.137)	(3.851)	(0.246)	(0.304)	(0.619)	(0.775)
BFG public	-	-1.292	-	-1.235	-	-1.074	-	0.799	-	-1.347	-	1.428
		(1.273)		(3.059)		(4.392)		(5.611)		(1.915)		(3.202)
BFG private formal	-	0.872	-	4.304	-	1.133	-	-0.310	-	-0.915	-	0.889
		(2.949)		(7.618)		(3.469)		(1.946)		(1.657)		(3.446)
BFG private informal	-	1.776*	-	-4.043	-	-1.035	-	0.922	-	0.789	-	1.253
		(1.068)		(3.992)		(1.953)		(1.857)		(0.685)		(2.442)
Observations	667		562		458		289		3,085		1,592	
R-squared	0.350	0.239	0.458	0.344	0.355	0.239	0.455	0.458	0.161	0.239	0.203	0.274

Source: Author's calculations (2024) based on KCHS (2021). Note: Individuals aged between 15 and 65 years. Bootstrapped standard errors for BFG regressions in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Note: the dependent variable is the logarithm of monthly earnings. Note: BFG public, BFG private formal, BFG private informal are the 3 selection correction terms (m_1, m_2, and m_3) corresponding to three alternatives of the outcome variable in the multinomial logit regression i.e., public sector, private formal sector, and private informal sector.
Note: Occ1- Legislatures, Administrators & Managers; Occ2- Professionals; Occ3- Technicians and associate professionals; Occ4- Clerical works; Occ5- Service workers, shop, and market sales; Occ6- Skilled agriculture, fishery, & forestry; Occ7- craft and trade related works; Occ8- Plant and machine operators and assemblers.

The results provide intriguing insights into labor market characteristics. Using the informal sector as the reference category (Table 12), both men and women are associated with higher wage premiums in the public sector compared to the private formal sector, with public sector earnings being more favorable. Notably, these premiums are significantly higher for women than men in both sectors. Across age cohorts (Table 14), the public sector is associated with a higher wage premium than the private formal sector. For workers aged 15–34, the earnings premium in both sectors is greater for women than men, while for those aged 35+, the association is more pronounced for men. Also, using occ9: elementary occupations as the reference category, the "legislators, administrators, and managers" category is associated with a positive wage premium in the public sector, with a slightly stronger association for women than men (Table 13).

The results further indicate that working as a "professional" is associated with a positive wage premium for men across all employment sectors. In the private formal and informal sectors, the occupation category "technicians and associate professionals" significantly boosts men's earnings, while in the public sector, the association is stronger for men than women. Similarly, the category "service workers, shop and market workers" is associated with an earnings advantage for men in the public and private formal sectors, but in the informal sector, the association is significant yet inverse for women. As expected, traditionally male-dominated occupations like "craft and trade-related work" and "plant and machine operators and assemblers" are associated with a wage premium for men in the public sector. Conversely, the female-dominated category "skilled agriculture, fishery, and forestry" is associated with a wage disadvantage for women in the private casual sector. All in all, the associations vary significantly across occupations, industries, age cohorts, and gender, supporting labor market segmentation and occupational crowding theories. These findings highlight the effect of occupational and industrial segregation on wages, aligning with existing literature (Agesa et al., 2013; Omanyo, 2021; Kwenda & Ntuli, 2018; Kolev & Robles, 2010).

The average weekly hours worked in the primary occupation is positively and significantly associated with earnings for both men and women in the full sample. However, in the public and private formal sectors, hours of work is negatively associated with men's earnings. Structural dynamics in Kenya's labor market may explain why longer work hours is associated with lower compensation, especially in EPZs and informal sector, aligning with the observed inverse correlation in our results. Firm size, measured by the number of workers, is significantly associated with earnings for both men and women in the informal sector and across all age cohorts. However, the association is positive and significant only for women in the public sector and only for men in the private formal sector. Using rural residence as the reference category, urban residence is associated with significantly higher wages in the informal sector and across age cohorts, with a more pronounced association for younger women than men.

For men, marriage is associated with higher earnings in the full sample and private formal sector, reflecting societal perceptions of married men as more stable and motivated, which can positively influence employers' decisions (Ntuli, 2007). In contrast, marriage is negatively associated with women's earnings in the full sample and informal sector, largely due to the "second shift" burden—balancing domestic responsibilities with paid work. And marriage is also positively associated with earnings for older workers (35+ years), especially men, as it signals stability and productivity to employers. However, in the public sector, marriage has no significant association with earnings for either gender. This is likely due to the implementation of anti-discrimination policies and initiatives promoting equal pay for equal work, as outlined in Kenya's Employment

Act of 2007. Public sector compensation is primarily merit-based, determined by qualifications, skills, experience, and industry rather than marital status. That said, these findings do not entirely rule out the presence of taste-based or statistical discrimination within Kenya's public sector.

Table 14: OLS and Selectivity Corrected (Heckman's two step) Log earnings equations by gender across age cohorts.

	15-34 years				35+ years			
	Men		Women		Men		Women	
	OLS	Heckman	OLS	Heckman	OLS	Heckman	OLS	Heckman
Potential experience	0.0472*	0.0420*	0.00611	0.00303	0.0368*	0.0322	0.0256	0.0248
	(0.0249)	(0.0250)	(0.0286)	(0.0286)	(0.0221)	(0.0223)	(0.0292)	(0.0293)
Experience square	-0.00222	-0.00203	0.00216	0.00228	-0.000641	-0.000497	-0.000550	-0.000523
	(0.00206)	(0.00206)	(0.00239)	(0.00239)	(0.000429)	(0.000437)	(0.000591)	(0.000594)
Married	0.0439	0.118*	-0.170**	-0.114	0.178**	0.339***	-0.0591	-0.0241
	(0.0619)	(0.0714)	(0.0692)	(0.0790)	(0.0804)	(0.127)	(0.0712)	(0.102)
Household size	-0.0381***	-0.0502***	-0.0192	-0.0284*	-0.0532***	-0.0619***	-0.0435***	-0.0462***
	(0.0112)	(0.0126)	(0.0139)	(0.0152)	(0.0116)	(0.0128)	(0.0158)	(0.0168)
Urban	0.161***	0.135**	0.300***	0.282***	0.0621	0.0365	0.180**	0.174**
	(0.0621)	(0.0633)	(0.0754)	(0.0763)	(0.0612)	(0.0631)	(0.0779)	(0.0790)
Christian	0.179*	0.180*	0.0899	0.107	0.303***	0.303***	0.210	0.208
	(0.0973)	(0.0972)	(0.211)	(0.211)	(0.114)	(0.114)	(0.241)	(0.241)
Islamic	0.405***	0.404***	0.372	0.390	0.762***	0.762***	0.485	0.483
	(0.135)	(0.135)	(0.258)	(0.258)	(0.151)	(0.151)	(0.305)	(0.305)
Firm size	0.121***	0.124***	0.0869***	0.0865***	0.104***	0.105***	0.110***	0.110***
	(0.0178)	(0.0178)	(0.0221)	(0.0221)	(0.0165)	(0.0165)	(0.0216)	(0.0216)
Hours of work	0.00836***	0.00802***	0.00932***	0.00899***	0.00724***	0.00709***	0.0119***	0.0119***
	(0.00159)	(0.00160)	(0.00206)	(0.00207)	(0.00169)	(0.00169)	(0.00244)	(0.00244)
Tenure	-0.00347	-0.00246	0.0319	0.0323	0.0119	0.0123	0.000280	0.000508
	(0.0178)	(0.0178)	(0.0209)	(0.0209)	(0.00907)	(0.00907)	(0.0111)	(0.0111)
Tenure square	0.000719	0.000640	-0.00167	-0.00171*	-0.000296	-0.000308	0.000211	0.000205
	(0.000953)	(0.000953)	(0.00103)	(0.00103)	(0.000274)	(0.000274)	(0.000326)	(0.000327)
Public sector	0.557***	0.545***	0.803***	0.807***	0.622***	0.616***	0.487***	0.486***
	(0.137)	(0.137)	(0.144)	(0.144)	(0.112)	(0.112)	(0.167)	(0.167)
Private formal	0.395***	0.388***	0.423***	0.432***	0.385***	0.378***	0.357**	0.354**
	(0.101)	(0.101)	(0.120)	(0.120)	(0.106)	(0.106)	(0.160)	(0.160)
Primary education	-0.0912	-0.0953	-0.280	-0.292	-0.257	-0.257	-0.608*	-0.606*
	(0.169)	(0.169)	(0.286)	(0.286)	(0.196)	(0.196)	(0.326)	(0.326)
Secondary education	0.169	0.171	0.101	0.0965	-0.0201	-0.0174	-0.274	-0.269
	(0.168)	(0.168)	(0.284)	(0.284)	(0.199)	(0.199)	(0.329)	(0.329)
Diploma	0.374**	0.242	0.424	0.331	0.672***	0.540**	0.304	0.277
	(0.184)	(0.195)	(0.289)	(0.295)	(0.217)	(0.231)	(0.339)	(0.344)
Bachelor's degree	0.810***	0.683***	0.967***	0.880***	1.038***	0.906***	0.692*	0.666*
	(0.208)	(0.216)	(0.311)	(0.316)	(0.232)	(0.245)	(0.356)	(0.360)
Postgraduate degree	1.688***	1.552***	2.167***	2.098***	1.706***	1.573***	1.085***	1.059***
	(0.575)	(0.579)	(0.575)	(0.576)	(0.297)	(0.308)	(0.405)	(0.409)
Occ1	0.194	0.215	0.0771	0.103	0.558***	0.561***	0.565**	0.566**
	(0.289)	(0.289)	(0.309)	(0.310)	(0.210)	(0.210)	(0.282)	(0.282)
Occ2	0.302*	0.315*	-0.280*	-0.260	0.560***	0.565***	0.0324	0.0337
	(0.172)	(0.172)	(0.169)	(0.170)	(0.160)	(0.160)	(0.192)	(0.192)
Occ3	0.400**	0.415**	0.132	0.162	0.615***	0.622***	0.248	0.247
	(0.169)	(0.169)	(0.234)	(0.235)	(0.165)	(0.165)	(0.261)	(0.261)
Occ4	0.144	0.163	-0.0461	-0.0190	0.460	0.463	0.121	0.121
	(0.446)	(0.446)	(0.253)	(0.253)	(0.301)	(0.301)	(0.260)	(0.260)
Occ5	0.0322	0.0483	-0.288**	-0.264**	0.165	0.170	-0.118	-0.118
	(0.130)	(0.130)	(0.124)	(0.125)	(0.135)	(0.135)	(0.156)	(0.156)
Occ6	-0.350***	-0.339***	-0.607***	-0.589***	0.0943	0.0930	-0.346***	-0.345***
	(0.107)	(0.107)	(0.143)	(0.144)	(0.105)	(0.105)	(0.130)	(0.130)
Occ7	-0.0273	-0.0232	-0.0532	-0.0473	0.295**	0.299**	0.214	0.213
	(0.121)	(0.121)	(0.199)	(0.199)	(0.137)	(0.137)	(0.255)	(0.255)
Occ8	-0.00795	0.00345	-0.0659	-0.0595	0.344**	0.348**	-0.0667	-0.0634

	(0.134)	(0.134)	(0.275)	(0.275)	(0.149)	(0.149)	(0.368)	(0.368)
Unionization	0.148	0.145	0.299**	0.300**	0.177*	0.179*	0.341***	0.340***
	(0.140)	(0.140)	(0.149)	(0.149)	(0.0974)	(0.0974)	(0.116)	(0.116)
Primary sector	-0.0211	-0.0357	-0.901	-0.915	-0.273	-0.275	-0.134	-0.133
	(0.205)	(0.205)	(0.557)	(0.557)	(0.207)	(0.207)	(0.674)	(0.674)
Manufacturing	-0.0737	-0.0664	-0.667	-0.675	0.0724	0.0674	0.409	0.409
	(0.206)	(0.206)	(0.564)	(0.564)	(0.217)	(0.217)	(0.662)	(0.662)
tertiary_sector1	-0.0593	-0.0532	-0.466	-0.473	-0.0283	-0.0324	-0.398	-0.402
	(0.195)	(0.195)	(0.633)	(0.633)	(0.196)	(0.196)	(0.706)	(0.706)
tertiary_sector2	-0.0189	-0.0229	-0.757	-0.779	-0.0764	-0.0704	-0.0482	-0.0470
	(0.211)	(0.211)	(0.552)	(0.552)	(0.231)	(0.231)	(0.673)	(0.673)
tertiary_sector3	-0.222	-0.218	-0.460	-0.476	0.0968	0.0946	0.781	0.785
	(0.184)	(0.184)	(0.573)	(0.573)	(0.184)	(0.184)	(0.680)	(0.680)
tertiary_sector4	0.0872	0.0891	-0.738	-0.764	0.0568	0.0585	0.185	0.188
	(0.226)	(0.225)	(0.557)	(0.557)	(0.216)	(0.216)	(0.677)	(0.677)
tertiary_sector5	-0.103	-0.0994	-0.806	-0.828	-0.204	-0.198	0.169	0.170
	(0.215)	(0.215)	(0.547)	(0.547)	(0.212)	(0.212)	(0.667)	(0.667)
tertiary_sector6	0.261	0.230	-0.728	-0.766	0.361	0.315	-0.0226	-0.0244
	(0.261)	(0.261)	(0.553)	(0.553)	(0.285)	(0.286)	(0.678)	(0.471)
Written contract	0.770***	0.800***	0.787***	0.789***	0.680***	0.803***	0.720***	0.719***
	(0.0939)	(0.0984)	(0.0689)	(0.0690)	(0.0887)	(0.118)	(0.0709)	(0.0709)
Inverse of Mills ratio	-	-0.416**	-	-0.295	-	-0.384*	-	-0.0992
		(0.201)		(0.199)		(0.233)		(0.207)
Constant	7.378***	7.885***	8.299***	8.648***	7.075***	7.465***	7.666***	7.765***
	(0.298)	(0.386)	(0.651)	(0.692)	(0.410)	(0.473)	(0.867)	(0.891)
Observations	2,142	2,142	1,272	1,272	2,068	2,068	1,171	1,171
R-squared	0.288	0.289	0.437	0.438	0.430	0.431	0.558	0.558

Source: Author's calculations (2024) based on KCHS (2021). Note: Individuals aged 15 and above. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Note: the dependent variable is the logarithm of monthly earnings. Note: Occ1- Legislatures, Administrators & Managers; Occ2- Professionals; Occ3- Technicians and associate professionals; Occ4- Clerical works; Occ5- Service workers, shop, and market sales; Occ6- Skilled agriculture, fishery, & forestry; Occ7- craft and trade related works; Occ8- Plant and machine operators and assemblers.

To discuss the findings of the earnings determinants in the context of the Kenyan labor market, I first note that Kenya's emphasis on TVET and higher education aligns with the findings that advanced education significantly boosts earnings, particularly for women in the private formal sector. Postgraduate qualifications for women is strongly associated with a higher wage premium in the public sector, reflecting the government's efforts to bridge gender gaps in technical fields. However, the returns to education remain muted in the informal sector, where 81% of non-agricultural workers operate. This divergence underscores the persistent mismatch between Kenya's educational advancements and the limited absorption of skilled labor in informal, low-productivity activities. The "Silicon Savannah" digital economy and business process outsourcing industries, while growing, currently employ only 0.5% of the workforce, highlighting the need for broader formalization to utilize Kenya's educational gains.

The gender pay gap—women earn 81.1% of men's wages—is exacerbated by the informal economy's dominance, where 86% of women work compared to 77% of men. Informal jobs, often characterized by irregular hours and lack of union representation, disproportionately penalize women due to societal expectations around unpaid care work. The negative association of marriage with women's earnings in the informal sector reflects the "second shift" burden, where cultural norms assign domestic responsibilities to women, limiting their labor market participation. By contrast, the public sector's more equitable wage structure—where marriage's association with earnings is insignificant—demonstrates the potential of institutional policies to mitigate discrimination, as seen in the enforcement of the Employment Act of 2007.

Union membership correlates with a wage premium overall, but its association is uneven. In the public sector, where collective bargaining coverage is higher (44% of unionized employees), unions secure better wages and benefits, particularly for women. However, the informal sector—where labor laws are weakly enforced—has no significant union association with earnings, as wages are often determined by informal employer-employee agreements. This disparity aligns with the Labor Market Profile's observation that only 3.7% of total employment is covered by collective agreements, concentrated in formal sectors like education and public administration. The rise of gig economy platforms further complicates unionization efforts, as digital laborers face algorithmic management and precarious contracts, making their employment situation more vulnerable.

Urban residence is associated with a wage premium, reflecting the concentration of formal jobs in cities like Nairobi and Mombasa. However, rapid urbanization—projected to reach 50% by 2050—has intensified competition for decent jobs, particularly among youth. Occupational crowding persists, with men dominating higher-paying roles like "legislators, administrators, and managers," while women are overrepresented in lower-wage sectors like agriculture and domestic work. The wage penalty for women in "skilled agriculture" roles underscores the undervaluation of female-dominated sectors, despite agriculture's contribution to Kenya's GDP and employment.

The findings highlight the dual challenges of enhancing human capital returns and addressing systemic inequities. While Kenya's progressive legal framework, such as the 2010 Constitution and Gender Equality Commission, provides a foundation, implementation gaps persist. For instance, the proposed Unemployment Insurance Fund faces resistance due to overlapping levies, reflecting broader tensions between fiscal reforms and social protection. Similarly, the uneven distribution of health workers and limited access to social security (only 9% of Kenyans covered) exacerbates vulnerabilities for informal workers.

To sum up, the evidence suggests that observable factors, particularly human capital (e.g., education) and productivity-related characteristics, significantly associated with individual wages in Kenya. However, their association vary by gender, age cohort, and employment sector. Furthermore, controlling for selectivity bias in labor force participation and sectoral choice affects male-female earnings and, consequently, the gender pay gap. From these results, I note that Kenya's labor market is a mosaic of progress and paradox. While education and unionization offer pathways to equity, their benefits are constrained by informality, cultural norms, and uneven policy enforcement.

Fundamentally, the exclusion of human capital variables (e.g., education, potential experience, tenure) in Table A8 (Appendix) yields critical differences in the determinants of wages compared to the baseline models (Tables 12–14). These differences underscore the role of human capital in mediating wage disparities and shaping labor market outcomes. Notably, the wage penalty associated with female dummy widens significantly when human capital variables are omitted. The female coefficient in the Heckman model increases from -0.173 (baseline) to -0.201 (Table A8), implying that women's earnings penalty rises from 18.9% to 22.3% relative to men. This suggests that human capital endowments—particularly education and experience—explain a substantial portion of the observed wages. Their exclusion leaves a larger residual gap attributable to discrimination or unobserved factors. Additionally, union membership's wage premium increases markedly in the absence of human capital controls. For instance, the union coefficient rises from 0.275 (baseline) to 0.435 (Heckman, Table A8) for all workers, indicating that unionization's association with wages is conflated with human capital when the latter is omitted. Similarly, occupation and sectoral premiums (e.g., "legislators, administrators, and managers") become more pronounced, as these variables absorb part of the variance previously explained by education and experience.

The urban wage premium increases from 0.151 (baseline) to 0.195 (Heckman, Table A8), reflecting that urban advantages—such as access to formal jobs—are partially driven by higher educational attainment, which is no longer controlled for. Similarly, the public sector premium rises from 0.626 to 0.345 (OLS), suggesting that human capital disparities between public and informal sector workers underpin part of the baseline sectoral wages. And marriage transitions from having a negative association with women's earnings in the baseline models to a neutral or slightly positive effect in Table A8. This shift implies that the baseline penalty for married women (rooted in the "second shift" burden) is partially offset by their lower educational attainment or interrupted careers—factors excluded in Table A8.

The empirical evidence underscored the critical interplay between human capital endowments and job-related characteristics in shaping wage disparities. Human capital variables—such as education, experience, and tenure—are fundamental determinants of individual productivity and labor market outcomes. Their exclusion risks conflating structural inequities with unobserved heterogeneity, thereby inflating the unexplained component of the gender pay gap and distorting the estimated effects of institutional factors. For instance, omitting education and experience amplifies the apparent influence of unionization and occupational segregation, as these variables partially proxy for the omitted human capital traits.

Conversely, job characteristics—such as sectoral employment, firm size, and occupation—mediate the returns to human capital and reflect systemic barriers, including occupational crowding and sectoral stratification. Excluding these factors would obscure the mechanisms through which education and experience translate into wage differentials. For example, the higher returns to postgraduate qualifications for women in Kenya’s private formal sector are contingent on their access to high-productivity roles, which is itself shaped by labor market structures.

Thus, I integrate both human capital and job characteristics to disentangle the dual drivers of wage disparities. By doing so, I ensures robustness against omitted variable bias, enabling precise identification of structural inequities. Subsequent estimations and decomposition analyses therefore adopt this dual framework to isolate the contributions of observable traits, institutional dynamics, and unexplained discrimination—a methodological imperative validated by the stark contrasts between baseline model results and Table A8 results.

6.4.3 Standard Oaxaca mean decomposition of the sources of gender pay gap.

Next, the primary focus is to assess the partial impact of covariates and identify those with the strongest influence on the gender pay gap at the mean and across the entire wage distribution. To achieve this, I decompose the gender pay gap at the mean and each quantile into two components: namely composition effects and wage structure effects.

The descriptive and earnings regression analyses in the previous sections confirm the existence of a gender pay gap. To understand the factors responsible for this gap and proposing targeted interventions to reduce or eliminate it, here I decomposes the GPG into its underlying components. Using the standard Oaxaca-Blinder decomposition method and its extensions, I will analyze the contribution of observed characteristics at the mean earnings level. Then, I will use the reweighted RIF-Oaxaca decomposition procedure (Firpo et al., 2009, 2018) to examine the GPG across different points (deciles) of the earnings distribution.

I now turn to a discussion of the empirical results, beginning with the standard Oaxaca decomposition at the mean earnings level. This is followed by the Neumark decomposition, which addresses the "index number problem" inherent in the standard Oaxaca method. After, I examine the reweighted RIF-Oaxaca decompositions across different deciles of the wage distribution. In all the decompositions, other than potential experience, hours worked, unionization, the rest of the variables are grouped into eight aggregate sets—firm characteristics/size, education, occupation, region, sector of employment, residence, marital effects, and industry of work—to account for non-zero coefficient variance and simplify result interpretation. The contribution of each set is calculated as the sum of the contributions of its individual variables (Gang et al., 2021).

The results got from the standard Oaxaca and Neumark decompositions are presented in Table 15. This table provides coefficient estimates[9] and the percentage contribution of each covariate set to the aggregate gap. For clarity, the interpretation focuses on the percentage share, which shows the proportion of the gender pay gap driven by differences in observable productivity-related attributes versus differences in the returns to these attributes.

Table 15: Standard Oaxaca Decomposition of the Gender Pay Gap (Full sample)

	Earnings decomposition Adjusted by mills	
	Log Adjusted value	% Contribution
Mean of log male earnings	9.492***	
	(0.119)	
Mean of log female earnings	9.030***	
	(0.128)	
Gender pay gap	0.461***	100
	(0.176)	
Using male wage structure (Oaxaca-1)		
Composition effects	-0.0465	-10.2

[9] Note that a positive coefficient widens the gender wage gap while a negative coefficient narrows the wage gap.

	(0.0504)	
Wage structural effects	0.508***	110.2
	(0.176)	
Using female wage structure (Oaxaca-2)		
Composition effect	-0.0615	-13.3
	(0.0379)	
Wage structural effect	0.523***	113.4
	(0.171)	
Oaxaca-Ransom/Neumark decomposition		
Composition effect	-0.0427	-9.3
	(0.0382)	
Wage structural effect 1 (Overvaluation of male characteristics)	0.323***	70.1
	(0.0871)	
Wage structural effect 2 (Undervaluation of female endowments)	0.181**	39.3
	(0.0909)	

Source: Author's calculations (2024) based on KCHS (2021). Note: Individuals Aged 15 and above (Full sample). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Note: Number of observations with earnings = 6,632 and *SVY* specification is applied, hence the total sample population size = 5,390,236. The decomposition results are provided using both the male and female earnings structure (Oaxaca decomposition) and both simultaneously (Oaxaca-Ransom/Neumark), in absolute values as well as in proportions relative to the total earnings gap.

Table 15 presents compelling insights into the gender pay gap for the full sample[10]. After adjusting for selectivity bias in the earnings functions, the results confirm that women earn approximately 41.4% (= exp (0.461) - 1) of what men earn[11]. The composition and wage structural effects exhibit opposing signs and varying levels of significance, highlighting their distinct roles in shaping the observed earnings disparity. Of note, the wage structural effect—representing the portion of the gender pay gap attributable to differences in returns to observable characteristics—emerges as the dominant factor, accounting for 39.3% to 113.4% of the gap. In contrast, the composition effect, which captures differences in observable productivity-related characteristics between men and women, reduces the pay gap by only 9.3% to 13.3%. This stark contrast underscores the profound influence of unequal returns to characteristics, such as education and experience, in perpetuating gender pay inequality, far outweighing the effect of differences in observable attributes themselves.

[10] Without the *svy* (survey) specification, the log of mean earnings for men is 8.860, while for women it is 8.746, resulting in a gender pay gap of 0.114 log points. When adjusted for selectivity bias, this earnings gap increases to 0.382 log points. Incorporating the svy specification, the log mean earnings for men is 9.0263 and for women it is 8.932, yielding an unadjusted gender pay gap of 0.094 log points. However, the selectivity-adjusted earnings are significantly higher, at 9.494 for men and 9.030 for women, leading to a corrected gender earnings gap of 0.461 log points.

[11] The Selectivity-uncorrected log earnings for both men and women are underestimated compared to the selectivity-adjusted earnings. Consequently, the unadjusted gender pay gap of 0.094 log points is also an underestimate of the true pay differential, which is more accurately captured by the corrected 0.461 log points.

This means that while women workers often possess equal or superior productivity-related characteristics, they do not receive commensurate rewards in the labor market. The composition effect reduces the pay gap by only 9% to 13.3%. Meanwhile, male workers benefit from a significant structural advantage, as evidenced by the dominant wage structural effect, which accounts for 39.3% to 113.4% of the gap. This suggests that if men and women received equal returns for the same characteristics, a substantial portion of the gender pay gap—ranging from 39.3% to 113.4%—would be eliminated. These findings reveal a troubling reality: the gender pay gap is primarily driven by unequal treatment and differential returns for women, rather than differences in their productivity-related attributes. Whether this disparity stems from discrimination against women (using the female wage structure as the non-discriminatory benchmark) or favoritism toward men (using the male wage structure as the benchmark), the unexplained portion of the pay gap remains the key factor perpetuating inequality.

Somewhat paradoxically, the findings suggest that Kenyan women possess equal or superior productivity characteristics than their male counterparts, yet this advantage does not translate into higher earnings. The stark earnings disparity highlights the fact that the gender gap is primarily driven by the unequal valuation of women's skills and characteristics in the labor market, rather than by differences in productivity-related factors between men and women.

Using a non-discriminatory wage structure based on Neumark decompositions, the results align with the standard Oaxaca-Blinder findings, indicating an adjusted gender pay gap of 58.6%. The composition effect reduces the gap by approximately 9.3%, while the total wage structural effect—stemming from the undervaluation of women's observable characteristics and the overvaluation of men's—accounts for 109.4% (70.1 + 39.4) of the gap. Both the deviations of female (0.181) and male (0.323) returns from the pooled wage structure are significant, but the larger male deviation suggests that favoritism or nepotism toward men in returns to their productivity characteristics, is more pronounced than discrimination against women in Kenya's labor market. This implies that the overvaluation of men's returns provides them with a significant advantage, outweighing the undervaluation of women's returns to their characteristics. Despite evidence of nepotism favoring men, the persistent bias and unfavorable treatment in valuing women's characteristics remain a key driver of the gender pay gap. Compared to the standard O-B results, the gap would narrow by 10.2% to 13.3% if men and women had equal endowments.

However, the unexplained component still accounts for 110.2% to 113.4% of the total pay gap, overwhelmingly driving the disparity and highlighting the entrenched structural inequities in the labor market.

I will now conduct a detailed analysis in order to break down the composition and structural effects into key covariate sets, as presented in Table 16. A positive coefficient for a covariate tends to widen the gender wage gap, while a negative coefficient narrows it. The detailed decomposition shows that education and sectoral effects significantly contribute to the composition effect, thereby reducing the gender wage gap. In contrast, hours of work and occupational effects widen the gap through the composition effect. The largest contribution to gap reduction via the composition effect stems from differences in sectoral employment between men and women. Specifically, 6.2% to 6.8% of the gender pay gap can be attributed to differences in the distribution of men and women across employment sectors (public, private formal, and informal). This accounts for nearly a quarter (13.6% to 14.9%) of the explained pay gap, suggesting that equalizing the sectoral distribution of men and women could reduce the pay gap by approximately 15% through differences in observed characteristics.

These insights underscore the importance of addressing sectoral segregation to mitigate gender wage disparities. The literature supports the notion that sectoral choice is a critical predictor of the gender earnings gap. For instance, Fafchamps et al. (2006) found that the gender wage gap is largely driven by sorting among firms, while the education wage gap is primarily influenced by job selection. Similarly, Nordman et al. (2016) demonstrated that gender-specific sectoral location accounted for a significant portion of the gender wage gap in Madagascar in both 2001 and 2005. They attributed this finding to the higher proportion of women in the self-employed sector, where earnings are typically lower.

Table 16: A Detailed Decomposition of the sources of GPG

	Oaxaca-Blinder decomposition								Neumark decomposition					
	Male wage structure				Female wage structure						Male favoritism/Pure discrimination			
	Composition effect	Share (%)	Wage structural effect	Share (%)	Composition effect	Share (%)	Wage structural effect	Share (%)	Composition effect	Share (%)	Wage structural effect 1	Share (%)	Wage structural effect 2	Share (%)
Aggregate effects	-0.0465	-10.2	0.508***	110.2	-0.0615	-13.3	0.523***	113.4	-0.0427	-9.3	0.323***	70.1	0.181**	39.3
	(0.0504)		(0.176)		(0.0379)		(0.171)		(0.0382)		(0.0871)		(0.0909)	
Potential experience	0.0399**	8.7	-0.272*	-59.0	0.0162*	3.5	-0.248*	-53.8	0.0297***	6.4	-0.155**	-33.6	-0.107	-23.2
	(0.0156)		(0.159)		(0.00987)		(0.145)		(0.0108)		(0.0653)		(0.0893)	
Educational effects	-0.0601***	-13.0	-0.204**	-44.0	-0.0431***	-9.3	-0.221**	-47.9	-0.0501***	-10.9	-0.0829**	-18.0	-0.131*	-28.4
	(0.0170)		(0.0961)		(0.0118)		(0.104)		(0.0134)		(0.0303)		(0.0725)	
Sectoral effects	-0.0688***	-14.9	0.0916	19.9	-0.0628***	-13.6	0.0855	18.5	-0.0654***	-14.2	0.0403	8.7	0.0479	10.4

	(0.0142)		(0.173)		(0.0118)		(0.162)		(0.0115)		(0.0597)		(0.109)	
Industrial effects	-0.0241***	-5.2	-0.0437	-9.4	-0.0201***	-4.4	-0.0476	-10.3	-0.0207***	-4.5	-0.00640	-1.4	-0.0406	-8.8
	(0.00707)		(0.0590)		(0.00589)		(0.0643)		(0.00558)		(0.0240)		(0.0397)	
Occupational effects	0.0592**	12.8	-0.253*	-54.9	0.000474	0.1	-0.194*	-42.1	0.0282**	6.1	-0.120***	-26.0	-0.102	-22.1
	(0.0272)		(0.134)		(0.0155)		(0.103)		(0.0132)		(0.0342)		(0.0811)	
Marital effects	-0.0169*	-3.7	-0.222**	-48.2	0.0245***	5.3	-0.263**	-57	0.00388	0.8	-0.110***	-23.9	-0.132**	-28.6
	(0.00870)		(0.0601)		(0.00813)		(0.0713)		(0.00555)		(0.0274)		(0.0410)	
Religion effects	-0.00588	-1.3	0.0111	2.4	-0.00485	-1.1	0.0100	2.2	-0.00209	-0.5	-0.0296	-6.4	0.0369	8.0
	(0.0122)		(0.141)		(0.00484)		(0.127)		(0.00445)		(0.0251)		(0.106)	
Regional effects	-0.0160*	-3.5	-0.0691	-15.0	-0.0146*	-3.2	-0.0704	-15.2	-0.0153*	-3.3	-0.0345	-7.5	-0.0353	-7.7
	(0.00955)		(0.114)		(0.00870)		(0.116)		(0.00906)		(0.0404)		(0.0769)	
Firm characteristics	0.0112	2.4	0.0506	11.0	0.0123	2.7	0.0494	10.7	0.0122	2.6	0.00487	1.1	0.0447	9.7
	(0.00874)		(0.0914)		(0.00956)		(0.0892)		(0.00944)		(0.0313)		(0.0600)	
Hours of work	0.0588***	12.8	-0.130	-28.2	0.0407***	8.8	-0.112	-24.3	0.0554***	12	-0.106***	-23.0	-0.0209	-4.5
	(0.0144)		(0.116)		(0.00947)		(0.0999)		(0.00853)		(0.0396)		(0.0698)	
Unionization	-0.00459	-1.0	-0.00972	-2.1	-0.00357	-0.8	-0.0107	-2.3	-0.00403	-0.9	-0.00436	-0.9	-0.00592	-1.3
	(0.00603)		(0.0104)		(0.00471)		(0.0115)		(0.00528)		(0.00372)		(0.00750)	
Constant			1.466***	318			1.466***	318			0.868***	188.3	0.598**	129.7
			(0.399)				(0.399)				(0.160)		(0.262)	
Observations	6,632		6,632		6,632		6,632		6,632		6,632		6,632	

Source: Author's calculations (2024) based on KCHS (2021). Note: Individuals aged 15 and above (Full sample). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Note: Number of observations with earnings = 6,632 and *SVY* specification is applied. Note: Each category summarizes the contribution of the sum of individual effects. 'Firm characteristics' summarizes the contribution of different firm sizes. 'Marital effect' captures the combined effect of marital status; married, cohabiting, separated/divorced/widow/er, or single. 'Regional effect' summarizes the effect of dummies representing urban and rural localities. 'Religion effects' adds dummies for various religions in Kenya. 'Sectoral effects' bands together dummy for broad sectors of employment. 'Occupational effects' captures the effects of various occupations. 'Industrial effect' summarizes the effects of various industries of work. 'Educational effects' bands together dummy variables for education categories. Note: Share is computed as a proportion of the estimated gender pay gap.

Interestingly, the contribution of education to the gender pay gap through the composition effect is negative, indicating that educational attributes significantly reduce the GPG by 9.3% to 13% in relative terms. This suggests that women possess better educational attainments than men, and if these observable characteristics were equally rewarded, the pay gap would decrease by nearly a quarter. This underscores the positive impact of government efforts to achieve gender parity in education and access to TVET and higher education. On the other hand, differences in potential work experience between men and women account for 3.5% to 8.7% of the GPG. This reflects the fact that men, being older in the dataset, tend to have more potential experience in their current occupations compared to women, thereby widening the pay gap. Together, these results emphasize the dual role of education and experience in shaping the GPG, with education acting as a mitigating factor and experience as a contributing factor to the disparity. These findings align with existing literature (Agesa et al., 2013; Omanyo, 2021; Kolev & Robles, 2010), which generally highlights the persistent influence of experience disparities on gender wage inequality.

The results also underscore the significance of the composition effect in gender differences in industrial choice as a determinant of the pay gap. Gender differences in industrial choice contribute approximately 2.4% to the reduction of the gap, accounting for roughly 4.4% to 5.2%

of the pay gap explained by the composition effect. This suggests that a small portion of the gap can be attributed to the differential sorting of men and women into various sectors or industries. The female advantage in industry variables indicates that many women are concentrated in better-remunerated sectors or industries (high proportion of women in education and healthcare) compared to men, which helps reduce the gender pay gap. This discrepancy highlights the complexity of sectoral dynamics and the need for context-specific analysis to understand how industrial choice influences gender wage disparities. While the current results point to a female advantage in certain sectors, broader structural barriers and sectoral segregation in other contexts may still perpetuate gender inequality in earnings. This finding aligns with the results of Campos and Gassier (2015), who observed similar patterns in certain contexts. However, this stands in stark contrast to existing evidence from developing countries, which often suggests that sectors where women are concentrated tend to be more crowded, with lower profits and growth potential compared to male-dominated sectors (Carranza et al., 2018).

In addition to the significant roles of education and sectoral choice, other factors contributing to the reduction of the gender pay gap through the composition effect include gender differences in marital status and regional residence. However, compared to education and industrial choice, these factors play a relatively minor role, accounting for just over 3 percentage points in the relative reduction of the pay gap. On the other hand, significant factors that widen the gender pay gap through the composition effect are occupational segregation and differences in weekly hours of work. Gender disparities in weekly hours of work account for 12% of the explained gender pay gap, while the uneven distribution of men and women across occupations—driven by occupational segregation—contributes 6.1% to 12.8% to the GPG. These findings highlight how occupational crowding and the unequal allocation of working hours between genders exacerbate earnings disparities.

Given that the bulk of the gender earnings gap is driven by the wage structural effect, it is crucial to examine which factors contribute to widening this gap. The structural effect is primarily explained by unobserved or unidentified traits between men and women, as evidenced by the large, positive, and statistically significant coefficients of the intercept term. These unobserved factors account for 129.7% to 318% of the pay gap through the structural effect, highlighting the pervasive influence of hidden biases or systemic inequalities in the labor market. Among the observable variables, sectoral effects stand out as a significant contributor to the widening of the pay gap. On their own, sectoral effects contribute 4% to 9.2% to the increase in the pay gap, accounting for 8.7% to 19.9% of the gap explained by the structural effect. This suggests that the returns to sectoral employment disproportionately favor men, most likely due to their overrepresentation in higher-paying sectors or roles.

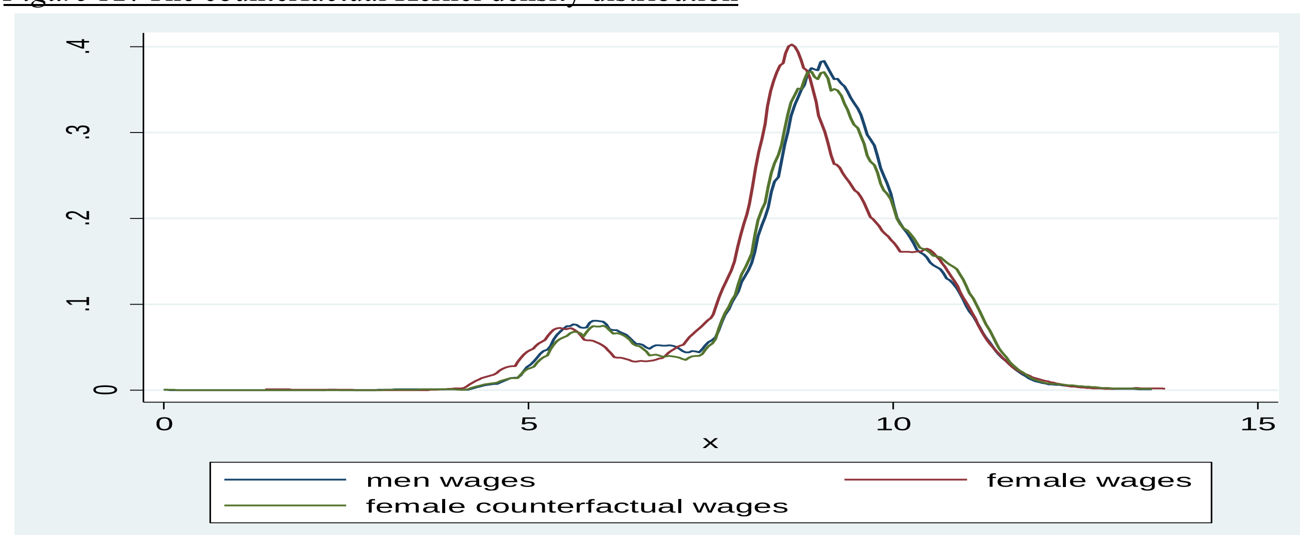
In contrast, other covariates—such as potential experience, education, occupational effects, industrial effects, marital status, hours of work, and regional effects—contribute to reducing the pay gap through the structural effect. This indicates that the returns to these observable characteristics are more favorable for women. For instance, women may be more likely than men to work in urban areas within the informal sectors, though with unregulated wage laws and no social protection, the earnings are tax free. And women with higher educational attainments may be more concentrated in skilled, better-paying occupations (e.g., high representation of women in managerial roles, education etc.), further narrowing the gap.

6.4.4 Female Counterfactual earnings Distributions

Before decomposing the gender pay gap into composition and wage structure effects using the reweighted Oaxaca-RIF decomposition, I first compute female counterfactual earnings. These counterfactual earnings represent what female workers would earn if they had the same distribution of observed and unobserved characteristics as male workers across all quantiles. This counterfactual serves as a benchmark to estimate the GPG. Kernel density estimates of the female counterfactual earnings distribution, alongside the actual male and female earnings distributions, are depicted in Figure 12. The female counterfactual earnings density is more "bell-shaped" compared to the actual female wage density and aligns more closely with the male earnings density in terms of peak location. However, the female counterfactual density shows less rightward translation compared to the male density, except in the upper half of the earnings distribution. Despite this, the gap between the two densities remains relatively narrow, reflecting the gender differences in observed characteristics or composition effects (Agesa et al., 2013; Firpo et al., 2009, 2018). In contrast, visual estimates of the kernel density earnings for female employees and the kernel density earnings for female counterfactual earnings indicate that the female counterfactual wage density exhibits a rightward translation across the entire earnings distribution. The gap between these two densities reflects gender differences in the returns to characteristics, or wage structure effects, and it is notably wider, particularly at the bottom, middle, and upper halves of the distribution.

Taken together, these observations suggest that if female workers retained their productivity characteristics but renumerated using male wage structure, the gender pay gap would significantly narrow across the earnings distribution. However, caution is warranted when interpreting the counterfactual wage densities in Figure 12. The relative position of female employees in the earnings distribution may shift compared to the original distribution, and the estimates may not fully capture discriminatory practices against women (Del Rı´o et al., 2011; Agesa et al., 2013). From a distributional perspective, Figure 12 may not accurately represent the discriminatory experiences faced by women workers and it should therefore be interpreted with care. Nevertheless, the use of the Oaxaca-RIF reweighting decomposition procedure provides a robust approximation of gender pay discrimination, offering valuable insights into the structural factors driving earnings disparities.

Figure 12: The counterfactual Kernel density distribution



Source: Author’s computation (2024) based on KCHS-2021 data

6.4.6 RIF-Oaxaca reweighting decomposition of the sources of GPG

The focus now shifts to the results derived from the RIF-Oaxaca decomposition, a novel approach that combines the RIF with the conventional Oaxaca decomposition method, enhanced by reweighting techniques. Similar to the standard Oaxaca decomposition, the RIF-Oaxaca method also provides insights into the contribution of each explanatory variable to both the composition and structural effects.

The findings are presented into two subsections. The first subsection examines the decompositions of the gender pay gap at the mean, across age cohorts and sectors of employment. This provides a broad overview of how observable characteristics and returns to those characteristics contribute to the pay gap in different demographic and employment contexts. The second subsection delves deeper, exploring whether the gender pay gap and its underlying determinants vary at different points (deciles) of the earnings distribution. Here, I present results across age groups and employment sectors, offering a more granular understanding of how earnings disparities manifest at various income levels. For each case, I not only decompose the overall gender pay gap into composition and structural effects but also provide a detailed breakdown of each effect by individual covariates.

Table 17 lists the results of the RIF-Oaxaca decomposition of gender differences in average earnings across age cohorts and sectors of employment. The first column in each category provides the estimates of the mean decomposition, while the second column shows the percentage share, indicating the contribution of specific covariates or groups of covariates to the gender pay gap. The "Counterfactual" component represents the estimated earnings distribution, illustrating what female earnings would have been if they had had the same coefficients as their male counterparts. The "pure composition and structural components" refer to the net differences after accounting for specification or reweighting errors, respectively.

A potential concern with the standard Oaxaca decomposition is its reliance on the assumption of linearity, which is critical for the consistent estimation of composition and structural effects (Firpo et al., 2018; Gang et al., 2021). However, the results in Table 17 demonstrate that the decomposition of the gender pay gap at the mean yields specification errors that are not statistically different from zero: 15-34 years cohort (0.00381), 35+ years cohort (-0.00206), public sector (-0.0294), private formal sector (0.104), and informal sector (0.0151). This suggests that the linear specification is empirically justified, and concerns about model misspecification can be dismissed. The reweighting errors are not significantly different from zero, indicating that the reweighting factors have been consistently estimated. These findings reinforce the robustness of the decomposition approach and provide confidence in the validity of the results.

Table 17: RIF-Oaxaca decomposition at the mean by age cohorts and sector of employment

	15-34 years		**35+**		**Public sector**		**Private formal sector**		**Informal sector**	
	Estimate	Share (%)	Estimate	Share (%)	Estimate	Share (%)	Estimate	Share (%)	Estimate	Share (%)
Mean male log earnings (M)	8.901***		9.062***		10.27***		9.947***		8.595***	
	(0.0295)		(0.0343)		(0.0410)		(0.0502)		(0.0246)	
Mean female log earnings (F)	8.810***		8.908***		10.21***		9.869***		8.246***	
	(0.0407)		(0.0477)		(0.0439)		(0.0737)		(0.0338)	
Gender Pay Gap (M-F)	0.0911*		0.154***		0.0616		0.0777		0.349***	
	(0.0503)		(0.0588)		(0.0600)		(0.0892)		(0.0418)	
Reweighting decomposition										
Counterfactual (C)	8.929***		9.217***		10.37***		9.996***		8.528***	
	(0.0307)		(0.0350)		(0.0386)		(0.0518)		(0.0250)	
Total composition effect (M - C)	-0.0277	-30.4	-0.155***	-100.6	-0.104*	-168.8	-0.0494	-63.6	0.0672*	19.3
	(0.0426)		(0.0490)		(0.0563)		(0.0721)		(0.0350)	
Total structural effect (C - F)	0.119**	130.6	0.309***	200.6	0.166***	269.5	0.127	163.4	0.282***	80.8
	(0.0510)		(0.0592)		(0.0584)		(0.0901)		(0.0420)	
RIF aggregate decomposition										
Pure composition effect	-0.0315	113.7	-0.134***	86.5	-0.0746*	71.7	-0.153***	309.7	0.0521***	77.5
	(0.0254)		(0.0320)		(0.0390)		(0.0501)		(0.0157)	
Specification error	0.00381	-13.7	-0.0206	13.3	-0.0294	28.3	0.104	-210.5	0.0151	22.5
	(0.0363)		(0.0385)		(0.0482)		(0.0651)		(0.0318)	
Pure wage structural effect	0.233***	195.8	0.208***	67.3	0.213***	128.3	0.0656	51.7	0.192***	68.1
	(0.0456)		(0.0496)		(0.0488)		(0.0862)		(0.0449)	
Reweighting error	-0.114***	95.8	0.101**	32.7	-0.0478	28.8	0.0615	48.4	0.0902***	32.0
	(0.0376)		(0.0471)		(0.0403)		(0.0610)		(0.0301)	
Pure composition effect										
Potential experience	0.0348**	-110.5	0.0276	-20.6	0.0861**	-115.4	0.0830	-54.2	0.0103	19.8
	(0.0171)		(0.0277)		(0.0431)		(0.0536)		(0.00760)	
Educational effects	-0.0272***	86.3	-0.0347***	25.9	-0.0792**	106.2	-0.227***	148.4	0.0202***	38.8
	(0.00738)		(0.0107)		(0.0215)		(0.0404)		(0.00473)	
Sectoral effects	-0.0172**	54.6	-0.0441***	32.9	-		-		-	
	(0.00730)		(0.0128)							
Industrial effects	0.00118	-3.7	-0.00949	7.1	0.00322	-4.3	0.00180	-1.2	0.00385	7.4
	(0.00237)		(0.00580)		(0.00343)		(0.00325)		(0.00319)	
Occupational effects	-0.000904	2.9	0.00412	-3.1	-0.00268	3.6	-0.000376	0.2	0.000264	0.5
	(0.00221)		(0.00318)		(0.00350)		(0.00267)		(0.00594)	
Marital effects	0.00499	-15.8	-0.00132	1.0	0.00469	-6.3	0.0217*	-14.2	0.00321	6.2
	(0.00319)		(0.00372)		(0.00590)		(0.0126)		(0.00230)	
Religion effects	0.00117	-3.7	-0.000312	0.2	0.000315	-0.4	0.00131	-0.9	0.00118	2.3
	(0.00147)		(0.000943)		(0.00217)		(0.00626)		(0.00131)	
Regional effects	0.0128	-40.6	-0.00319	2.4	0.000223	-0.3	-0.000392	0.3	0.0143**	27.4
	(0.00826)		(0.00305)		(0.00616)		(0.00803)		(0.00713)	
Firm characteristics	-0.00542	17.2	-0.0163**	12.2	-0.000706	0.9	-0.00180	1.2	0.00544	10.4
	(0.00702)		(0.00816)		(0.00771)		(0.00445)		(0.00560)	
Hours of work	0.00494	-15.7	0.00295	-2.2	-0.0163**	21.8	-0.0119	7.8	0.00521	10.0
	(0.00320)		(0.00340)		(0.00770)		(0.00809)		(0.00502)	
Unionization	0.000654	-2.1	-0.00741*	5.5	-0.00722	9.7	0.00282	-1.8	0.000225	0.4
	(0.00263)		(0.00394)		(0.0121)		(0.00831)		(0.00543)	
Mills ratio (selectivity correction term)	-0.0168**	53.3	-0.0331***	24.7	-0.0368*	49.3	-0.00404	2.6	-0.00472*	-9.1
	(0.00828)		(0.00892)		(0.0198)		(0.0187)		(0.00279)	
Pure structural effect										
Potential experience	0.263	112.9	0.468	225.0	0.0736	34.6	0.00775	11.8	-0.171	-89.1
	(0.180)		(0.829)		(0.291)		(0.288)		(0.145)	
Educational effects	-0.252***	-108.2	-0.0473	-22.7	0.0106	5.0	-0.600***	-914.6	-0.0857	-44.6

	(0.0921)		(0.102)		(0.167)		(0.198)		(0.0758)	
Sectoral effects	0.154	66.1	0.0884	42.5						
	(0.201)		(0.204)							
Industrial effects	-0.0873	-37.5	0.0227	10.9	-0.0293	-13.8	0.161	245.4	-0.0436	-22.7
	(0.0839)		(0.0769)		(0.205)		(0.195)		(0.0627)	
Occupational effects	-0.335***	-143.8	0.0279	13.4	0.00553	2.6	-0.253*	-385.7	-0.345**	-179.7
	(0.109)		(0.133)		(0.0743)		(0.153)		(0.156)	
Marital effects	-0.300***	-128.8	-0.253***	-121.6	-0.121	-56.8	-0.463***	-705.8	-0.233***	-121.4
	(0.0796)		(0.0937)		(0.0750)		(0.163)		(0.0791)	
Religion effects	-0.0376	-16.1	-0.00638	-3.1	-0.267*	-125.4	0.345	525.9	0.0692	36.0
	(0.113)		(0.124)		(0.140)		(0.292)		(0.109)	
Regional effects	-0.0178	-7.6	-0.169	-81.3	-0.231	-108.5	-0.401	-611.3	-0.141	-73.0
	(0.142)		(0.133)		(0.157)		(0.373)		(0.124)	
Firm characteristics	0.0543	23.3	-0.0779	-37.5	-0.252	-118.3	-0.0428	-65.2	0.0307	16.0
	(0.0995)		(0.103)		(0.171)		(0.327)		(0.0718)	
Hours of work	-0.135	-57.9	-0.190	-91.3	-0.413**	-193.9	-0.189	-288.1	0.0463	24.1
	(0.114)		(0.122)		(0.191)		(0.265)		(0.0998)	
Unionization	-0.00609	-2.6	-0.0138	-6.6	-0.0665*	-31.2	0.0138	21.0	-0.000691	-0.4
	(0.00988)		(0.0210)		(0.0366)		(0.0211)		(0.00347)	
Mills ratio (selectivity correction term)	-0.182	-78.1	-0.377*	-181.3	-0.288	-135.2	-0.504*	-768.3	-0.199	-103.6
	(0.180)		(0.206)		(0.225)		(0.286)		(0.182)	
Intercepts	1.341***	575.5	0.909	437.0	1.771***	831.5	2.024**	3085.4	1.211***	630.7
	(0.428)		(0.629)		(0.506)		(0.797)		(0.375)	
Observations	3,414		3,239		1,229		747		4,677	

Source: Author's calculations (2024) based on KCHS-2021. Note: Individuals aged 15 and above (Full sample). Robust standard errors in parentheses are robust to heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1 denote significance at the 1, 5, and 10 per cent levels, respectively. Note: Sampling weights are used in estimations. Note: the dependent variable is the logarithm of monthly earnings. The reweighting factors are estimated using a logit model. Counterfactual (C) is the estimated distribution of earnings, showing female mean earnings if they had the same coefficients as their male counterparts. The total composition effect refers to the part of the Gender pay gap due to gender differences in characteristics/endowments. Total structural effect refers to the part of the wage gap due to gender differences in returns to those characteristics. The pure composition effect and pure structural effect are the net differences of specification error and reweighting error, respectively.

I shall first discuss the decomposition results across different sectors of employment, followed by an analysis across age cohorts. The findings (Table 17) indicate that women, on average, face significant earnings disadvantages, with the most pronounced pay penalty observed in the informal sector. Here, the gender pay gap stands at 0.349 log points, or 41.8%[12], followed by the private formal sector, where the GPG is 0.0777 log points, or 8.1%. Interestingly, the public sector exhibits the lowest GPG, at 0.0616 log points, or 6.4%. However, it should be remarked that the GPG in the public and private formal sectors is not statistically significant at the mean. The substantial GPG in the informal sector highlights the ineffectiveness of the "equal-pay-for-equal-work" policy in this sector compared to the formal sector. This disparity underscores the challenges women face in informal employment, where labor regulations are weakly enforced, and wage disparities are more pronounced. In contrast, the relatively lower and statistically insignificant GPG in the formal sector suggests that institutional policies and stronger enforcement mechanisms may play a role in mitigating wage inequality.

[12] The percentage figure is calculated as $(e^{0.349} - 1) \times 100$.

Consistent with the results from the conventional Oaxaca decomposition for the full sample, the RIF-Oaxaca decomposition tells us that the structural effect accounts for the majority of the gender pay gap across all employment sectors. In the public sector, the structural effect explains 270% of the GPG, while in the private formal and informal sectors, it accounts for 163.4% and 80.8%, respectively. This provides strong evidence that in Kenya's private and informal sectors, which operate under competitive market models of profit maximization, statistical and taste-based discrimination persist. These findings highlight how systemic biases and unequal returns to characteristics adversely affect women, even when they possess comparable or superior endowments.

Regarding the composition effect, the results indicate that women have superior observable productivity characteristics than men, and if these differences were fairly rewarded, the entire pay gap (168.8%) in the public sector could be eliminated. In the private formal and informal sectors, the GPG could decline by more than half (63.6%) and one-fifth (19.3%), respectively. This underscores the potential of addressing gender disparities in observable characteristics, such as education and sectoral distribution, to reduce the earnings inequality. However, the persistent and dominant role of the structural effect across all sectors emphasizes that discrimination—whether through unequal returns to characteristics or systemic biases—remains a significant driver of the GPG.

For the pure composition effect, gender differences in education, potential experience, regional effects, hours of work, and the selectivity correction term significantly contribute to the gender pay gap. Specifically, gender differences in education could reduce the GPG by 106.2% through the composition effect, suggesting that women possess better educational attainments, which are highly rewarded, particularly in the public sector. However, consistent with descriptive results, gender differences in potential experience and hours of work—which favor men—widen the pay gap by 115.4% and 21.8%, respectively, through the composition effect in the public sector.

Likewise, in the private formal sector, gender differences in education and potential experience account for a 148.4% reduction in the GPG through the composition effect. This indicates that women's superior educational attainment has played a significant role in narrowing the gender pay gap in this sector. In the informal sector, gender differences in education contribute to a 38.8% reduction in the GPG, while regional effects explain approximately 27% of the gap.

These results underscore the dual role of education as a mitigating factor and experience/working hours as contributing factors to wage disparities, while also emphasizing the importance of regional dynamics in shaping gender pay inequality, particularly in the informal sector.

Surprisingly, in the public sector, accounting for selectivity bias in labor force participation and sectoral choice reduces the gender pay gap by 49.3% through the composition effect. This suggests that addressing unobservable factors that may limit women's participation in the public sector could significantly contribute to narrowing the GPG. Conversely, in the informal sector, the selectivity correction term increases (widens) the gap by 9.1% through the composition effect. This widening effect may stem from the exclusion restriction related to household size (number of children), which often leads women to prioritize domestic responsibilities over market labor, especially in the private informal sector.

In the private formal sector, gender differences in the returns to education significantly widen the gender pay gap through the structural effect. This indicates that women's higher educational attainment is undervalued in this sector, as their qualifications are not adequately rewarded compared to men's. Similarly, differences in the returns to occupation account for a significant portion of the pay gap in both the private formal and informal sectors. This reflects the tendency for women to be concentrated in lower-paying jobs, exacerbating pay disparities. And the structural effect makes clear that marital status positively contributes to the pay gap in the private formal and informal sectors. This suggests that married men benefit from an earnings premium, most likely due to traditional gender norms and societal expectations that favor men as primary breadwinners. Lastly, in the public sector, gender differences in the returns to region of residence favor men, as they enjoy a wage premium over women.

The results of the gender pay gap across different age groups provide both interesting and anticipated findings. The pay disparity is significantly more pronounced among older workers aged 35 and above, nearly twice as large as the gap observed among younger workers aged 15-34. While younger women earn, on average, around 90.5% of their male counterparts' earnings, this figure drops to 83.4% for older female workers. Delving deeper, the composition effect—which captures the influence of observable characteristics—accounts for a substantial 30.4% reduction in the pay gap among younger workers. However, for older workers, these same endowments would eliminate the entire gender pay gap. This suggests that while younger women benefit from better alignment in observable characteristics, older women face a more entrenched wage disparity, most likely due to cumulative structural biases and unequal returns to experience over time. Interestingly, the wage structural effect emerges as the dominant factor driving the pay gap in both age groups. For younger workers, this wage structural effect alone explains the entire (130%) observed gap, while for older workers, it accounts for a staggering 200% of the gap. This means that the discrimination effect, along with other underlying factors contributing to the pay gap, is substantial, even exceeding the entire observed disparity for both younger and older workers.

Looking at the covariates underlying the composition effect (endowment effect) of the gender pay gap provides valuable insights. The effect of education in reducing the pay gap is more significant among younger workers (86.3%) compared to older workers (25.9%). However, gender differences in potential work experience emerge as a factor that widens the pay gap through the composition effect. This effect is more pronounced among younger workers (110.5%) compared to older cohorts (20.6%). This suggests that while gender disparities in potential work experience exist, they are less prevalent among older workers and do not contribute as significantly to wage disparities in this age group.

Regarding job characteristics, the sectoral choice of employment reduces the gender pay gap by 54.6% among younger workers and 32.9% for older workers. Among younger workers, selection into specific occupations and firms further reduces the GPG by 3% and 17.2%, respectively. However, factors such as industry of work, hours of work, region of residence, marital status, and religion increase the pay gap by 3.8%, 15.2%, 40.6%, 15.8%, and 3.7%, respectively. For older workers, industrial choice, marital status, religion, union membership, and firm characteristics all contribute to reducing the pay gap through the composition effect, by 7.1%, 1%, 2.4%, 5.5%, and 12.2%, respectively. Interestingly, marriage and union membership are found to reduce the pay gap among older workers but not among younger workers. This may reflect the stabilizing effect of marriage and union representation on earnings for older workers, who are more likely to be established in their careers. As for the pure wage structural effect, gender differences in returns to education are found to widen the GPG. This suggests that women's educational attainment is undervalued in the Kenyan labor market, with this effect being more pronounced among younger workers compared to older workers.

6.4.7 Decomposition at Unconditional Quantiles by Age Cohorts and Sector of employment.

To better understand how the gender pay gap evolves across the earnings distribution, I evaluate the GPG at each decile, disaggregated by age cohorts and employment sectors. This allows us to examine the contribution of each covariate to the GPG at different points in the distribution, both as part of the composition effect and the structural effect. Table 18 gives the earnings gap estimates and aggregate RIF-Oaxaca decompositions at each decile, while

Figure 13 provides a graphical representation of the key results, reinforcing the findings.

The findings highlight the importance of analyzing the gender pay gap and its drivers across the entire earnings distribution, as average GPG figures often mask subtle variations. The age cohort results yielded unexpected insights. Specifically, the GPG is unevenly distributed across earnings for both the 15-34 and 35+ age groups. For the 15-34 cohort, the GPG rises from the bottom to the median but declines in the top deciles. Also, the GPG is positive across all earnings levels except the first decile, with statistically significant gaps observed only between the 30th and 80th percentiles.

For the 15-34 age group, the gender pay gap increases gradually from the bottom of the earnings distribution, peaking at the 50th percentile with a value of 0.210 log points or 23.4%. Beyond this point, it declines steadily but remains statistically significant up to the top deciles, except at the 90th percentile, where it becomes insignificant. These patterns indicate that the GPG is largest in the middle deciles for this age group, narrowing significantly at both the top and bottom of the distribution[13]. Notably, the GPG at the 50th percentile is 12% higher than the mean GPG of 0.0911 log points (9.5%) reported in Table 17. And the GPG between the 30th and 80th percentiles consistently exceeds the average GPG for the 15-34 cohort.

Table 18: Decomposing GPG by percentiles and age cohorts: RIF-Oaxaca aggregate decomposition

Age 35+	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	10%	20%	30%	40%	50%	60%	70%	80%	90%
Log Male earnings (M)	7.026***	8.368***	8.823***	9.062***	9.326***	9.720***	9.964***	10.35***	10.92***
	(0.135)	(0.0515)	(0.0341)	(0.0326)	(0.0330)	(0.0332)	(0.0358)	(0.0415)	(0.0466)
Log Female earnings (F)	7.115***	8.194***	8.488***	8.809***	9.141***	9.630***	10.01***	10.49***	10.97***
	(0.197)	(0.0558)	(0.0446)	(0.0474)	(0.0579)	(0.0655)	(0.0615)	(0.0553)	(0.0581)
Gender Pay Gap	-0.0882	0.174**	0.335***	0.254***	0.185***	0.0899	-0.0432	-0.138**	-0.0521

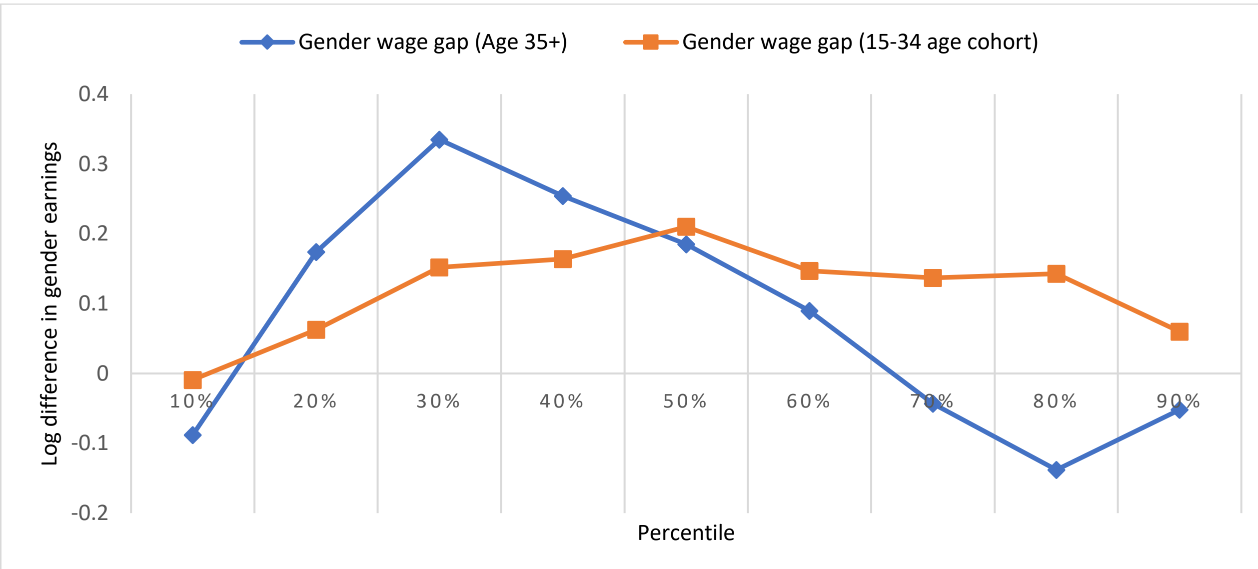
[13] This is confirmed by our results for the standard measures of the top-end (90–50 log wage differential) and the bottom-end (50–10 log wage differential) gender pay gap, as well as for the variance of log earnings and the Gini coefficient (see Appendix Table A3). The gender pay gap increases from the bottom decile to median deciles (50–10), although insignificant. At the top-end (90–50), the coefficient is negative and significant suggesting that the gender pay gap tends to narrow from the median deciles as we move up the top of the earnings distribution.

	(0.239)	(0.0759)	(0.0562)	(0.0575)	(0.0667)	(0.0735)	(0.0712)	(0.0692)	(0.0745)
Reweighting decomposition									
Counterfactual (C)	7.243***	8.503***	8.901***	9.213***	9.577***	9.847***	10.23***	10.64***	11.10***
	(0.138)	(0.0451)	(0.0360)	(0.0361)	(0.0361)	(0.0369)	(0.0406)	(0.0396)	(0.0437)
Total composition effect (M – C)	-0.216	-0.135**	-0.0776	-0.151***	-0.251***	-0.126**	-0.267***	-0.283***	-0.178***
	(0.193)	(0.0684)	(0.0496)	(0.0486)	(0.0489)	(0.0496)	(0.0541)	(0.0574)	(0.0639)
Total structural effect (C – F)	0.128	0.309***	0.412***	0.404***	0.436***	0.216***	0.224***	0.145**	0.126*
	(0.241)	(0.0717)	(0.0573)	(0.0596)	(0.0682)	(0.0752)	(0.0737)	(0.0681)	(0.0727)
RIF aggregate decomposition									
Pure composition effect	-0.192***	-0.114***	-0.0830***	-0.102***	-0.129***	-0.144***	-0.209***	-0.255***	-0.249***
	(0.0722)	(0.0353)	(0.0262)	(0.0277)	(0.0296)	(0.0303)	(0.0361)	(0.0432)	(0.0440)
Specification error	-0.0240	-0.0205	0.00533	-0.0489	-0.122***	0.0175	-0.0586	-0.0280	0.0711
	(0.187)	(0.0624)	(0.0429)	(0.0404)	(0.0394)	(0.0392)	(0.0405)	(0.0438)	(0.0541)
Pure structural effect	-0.267	0.0611	0.163***	0.170***	0.286***	0.164***	0.252***	0.288***	0.238***
	(0.266)	(0.0766)	(0.0571)	(0.0563)	(0.0581)	(0.0609)	(0.0598)	(0.0592)	(0.0722)
Reweighting error	0.395**	0.248***	0.249***	0.234***	0.150***	0.0523	-0.0284	-0.143***	-0.112**
	(0.156)	(0.0565)	(0.0476)	(0.0491)	(0.0503)	(0.0527)	(0.0584)	(0.0549)	(0.0556)
Age 15-34 years									
Log Male earnings (M)	6.703***	8.210***	8.703***	8.942***	9.182***	9.460***	9.714***	9.949***	10.38***
	(0.161)	(0.0539)	(0.0307)	(0.0270)	(0.0262)	(0.0262)	(0.0261)	(0.0282)	(0.0360)
Log Female earnings (F)	6.712***	8.147***	8.551***	8.778***	8.972***	9.313***	9.578***	9.806***	10.32***
	(0.246)	(0.0537)	(0.0337)	(0.0335)	(0.0377)	(0.0392)	(0.0367)	(0.0384)	(0.0622)
Gender Pay Gap	-0.00911	0.0627	0.152***	0.164***	0.210***	0.147***	0.137***	0.143***	0.0600
	(0.294)	(0.0761)	(0.0456)	(0.0430)	(0.0459)	(0.0471)	(0.0451)	(0.0477)	(0.0719)
Reweighting decomposition									
Counterfactual (C)	6.564***	8.208***	8.701***	8.959***	9.191***	9.478***	9.741***	9.973***	10.38***
	(0.106)	(0.0531)	(0.0313)	(0.0274)	(0.0269)	(0.0275)	(0.0280)	(0.0303)	(0.0358)
Total composition effect (M – C)	0.139	0.00202	0.00234	-0.0166	-0.00830	-0.0174	-0.0270	-0.0240	-0.00103
	(0.192)	(0.0756)	(0.0439)	(0.0384)	(0.0375)	(0.0379)	(0.0383)	(0.0415)	(0.0508)
Total structural effect (C – F)	-0.148	0.0607	0.149***	0.181***	0.218***	0.165***	0.164***	0.167***	0.0610
	(0.268)	(0.0755)	(0.0460)	(0.0432)	(0.0463)	(0.0478)	(0.0462)	(0.0489)	(0.0717)
RIF aggregate decomposition									
Pure composition effect	-0.0440	-0.0358	0.00663	0.00628	0.000996	-0.0115	-0.00728	-0.0436*	-0.0807***
	(0.0859)	(0.0346)	(0.0234)	(0.0226)	(0.0223)	(0.0225)	(0.0229)	(0.0238)	(0.0293)
Specification error	0.183	0.0378	-0.00429	-0.0228	-0.00930	-0.00595	-0.0197	0.0197	0.0797*
	(0.196)	(0.0725)	(0.0397)	(0.0333)	(0.0322)	(0.0324)	(0.0323)	(0.0357)	(0.0451)
Pure structural effect	0.105	0.225***	0.226***	0.256***	0.278***	0.257***	0.282***	0.289***	0.159**
	(0.274)	(0.0805)	(0.0467)	(0.0416)	(0.0426)	(0.0437)	(0.0423)	(0.0459)	(0.0663)
Reweighting error	-0.252**	-0.164***	-0.0764**	-0.0751**	-0.0598*	-0.0918***	-0.119***	-0.122***	-0.0978**
	(0.103)	(0.0562)	(0.0352)	(0.0320)	(0.0317)	(0.0328)	(0.0340)	(0.0369)	(0.0428)

Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The dependent variable is the estimated RIF at the respective decile of the log earnings. The gender wage gap is the difference between log male earnings and log female earnings. Sampling weights are used in the estimations. Standard errors reported in parentheses are robust to heteroskedasticity and clustered residuals within households. The reweighting factors are estimated using logit model. *** p<0.01, ** p<0.05, * p<0.1.

Among older workers (aged 35 and above), the gender pay gap also exhibits an uneven distribution. It rises sharply from the bottom decile to the 30th percentile before declining steadily from the 40th percentile to the top decile. Notably, in the top deciles, the gap turns negative and is statistically significant at the 80th percentile, indicating that older women earn more than their male counterparts in these higher earnings brackets. The GPG peaks at the 30th percentile (0.335 log points or 40%), more than double the mean GPG of 0.154 log points (or 16.7%). Unlike younger workers, the GPG for older workers is wider in the lower deciles and narrows significantly at the top[14], suggesting a "sticky floor" effect where older women are disproportionately concentrated in lower-paying roles. A key insight from the analysis is that the GPG at the lower end of the earnings distribution is much larger for older workers compared to younger ones, while at the upper end, younger workers face a more pronounced gap, and older women actually enjoy an earnings advantage.

Figure 13: A breakdown of gender pay gap by percentiles and age cohorts.



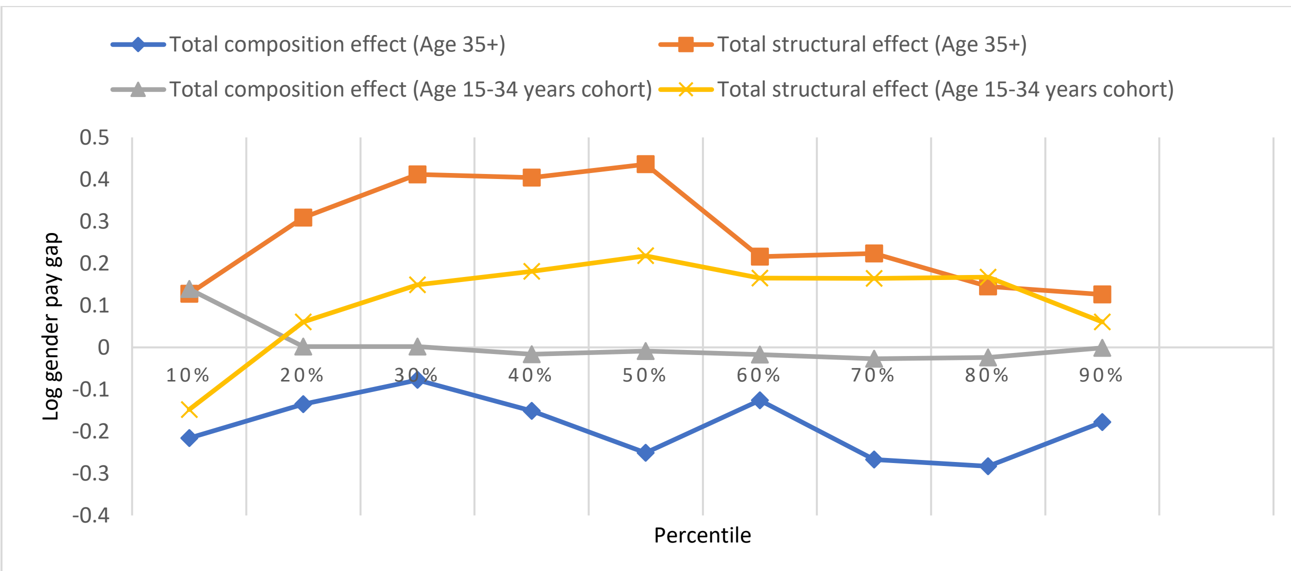
Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: Entries are based on the reweighted RIF-Oaxaca decomposition results presented in Table 19. The gender pay gap is the difference between log male earnings and log female earnings.

As with the mean gender pay gap (Table 17), the GPG across the earnings distribution is primarily driven by wage structural effects for both younger and older workers. However, the impact of the structural effect varies significantly at different points in the distribution. Notably, the structural effect plays a more substantial role among older workers (aged 35 and above) compared to younger workers (aged 15-34). For older workers, the structural effect is statistically significant from the 20th percentile to the top decile, with its contribution peaking between the 20th and 50th percentiles, where it accounts for 30% to 44% of the gap. In contrast, at the 90th percentile, the structural effect contributes only 12.6% (Table 18).

[14] This is also confirmed by our results for the standard measures of the top-end (90–50 log wage differential) and the low-end (50–10 log wage differential) gender pay gap, as well as for the variance of log earnings and the Gini coefficient (see Appendix, Table A3). The gender pay gap is highest, though insignificant, at the bottom-end (50–10), after which it significantly narrows towards the top-end (90–50), suggesting that the gender pay gap is highest at the low-end of the earnings distribution.

For younger workers (aged 15-34), the wage structural effect is statistically significant between the 30th and 80th percentiles. Its contribution peaks at the 50th percentile (22%), is lowest at the 30th percentile (15%) and amounts to 17% at the 80th percentile. While the absolute contribution of the structural effect varies across deciles, its relative importance remains fairly constant. Regarding the composition effect, gender differences in observed productivity-related endowments (e.g., education) consistently favor women[15] across the earnings distribution. This effect is more pronounced among older women compared to younger ones (Figure 14).

Figure 14: Wage structural and Composition effects by age groups.



Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: Entries are based on the reweighted RIF-Oaxaca decomposition results presented in Table 19.

The results in Table 19 reveal significant variations in the gender pay gap between male and female employees across the formal and informal sectors, with distinct patterns along the earnings distribution. The GPG is largest and statistically significant at all points in the informal sector compared to the public and private formal sectors (Figure 15). While the GPG is consistently high across the earnings distribution in the informal sector, it is particularly pronounced between the 60th and 80th percentiles. In the private formal sector, the GPG is widest at the lower end of the distribution, peaking at 0.356 log points (or 42.8%), before declining, albeit with some fluctuations across the earnings spectrum.

[15] Male wage is the non-discriminatory earnings structure. A negative wage gap means an advantage in favor of women.

Interestingly, at the 4th and 9th deciles, the coefficients are negative, indicating a GPG in favor of women, though this effect is statistically insignificant. As shown in Figure 15, the private formal sector exhibits a pronounced "sticky floor" effect, with women facing a wage penalty at the lower end of the earnings distribution, where the GPG is larger among low-wage employees[16]. In contrast, the public sector, which has the smallest GPG at the bottom of the earnings spectrum, shows a gradual increase in the gap from the 2nd decile, remaining stable up to the 7th decile, before sharply declining to -0.000243 log points (or reduces negligibly by 0.024%) at the 80th percentile. This suggests a slight earnings advantage for women, though it is statistically insignificant[17]. At the top of the earnings distribution, the GPG in the public sector is only 5 percentage points, compared to 26 percentage points in the private informal sector.

Altogether, the gender pay gap varies significantly across sectors and earnings levels. In the public sector, the GPG is largest in the middle of the distribution, reaching 16 percentage. In the private formal sector, the GPG peaks at the lower end of the distribution, at 36 percentage points. At the same time, in the informal sector, the GPG is highest at the 70th percentile. These patterns mean that the GPG is more pronounced at both the higher and lower ends of the earnings distribution in the informal sector compared to the public and private formal sectors.

Table 19: Decomposing by percentiles and sectors of employment: RIF-Oaxaca aggregate decomposition.

Public Sector	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	10%	20%	30%	40%	50%	60%	70%	80%	90%
Log Male earnings (M)	9.062***	9.485***	9.856***	10.21***	10.47***	10.65***	10.87***	11.02***	11.43***
	(0.0630)	(0.0651)	(0.0627)	(0.0570)	(0.0458)	(0.0414)	(0.0399)	(0.0394)	(0.0534)
Log Female earnings (F)	8.993***	9.403***	9.734***	10.04***	10.32***	10.52***	10.76***	11.02***	11.38***
	(0.0777)	(0.0681)	(0.0625)	(0.0569)	(0.0510)	(0.0487)	(0.0497)	(0.0533)	(0.0624)
Gender Pay Gap	0.0689	0.0818	0.122	0.177**	0.157**	0.135**	0.111*	-0.000243	0.0459
	(0.1000)	(0.0942)	(0.0886)	(0.0805)	(0.0686)	(0.0639)	(0.0638)	(0.0663)	(0.0822)
Reweighting decomposition									
Counterfactual (C)	9.213***	9.719***	9.980***	10.34***	10.57***	10.69***	10.88***	11.10***	11.47***
	(0.0637)	(0.0649)	(0.0600)	(0.0474)	(0.0400)	(0.0379)	(0.0373)	(0.0400)	(0.0538)
Total composition effect (M – C)	-0.151*	-0.234**	-0.124	-0.125*	-0.0999	-0.0326	-0.0134	-0.0847	-0.0389
	(0.0896)	(0.0919)	(0.0868)	(0.0741)	(0.0608)	(0.0561)	(0.0546)	(0.0561)	(0.0758)
Total structural effect (C – F)	0.220**	0.316***	0.246***	0.302***	0.256***	0.168***	0.124**	0.0844	0.0849
	(0.100)	(0.0941)	(0.0867)	(0.0741)	(0.0648)	(0.0617)	(0.0622)	(0.0666)	(0.0824)
RIF aggregate decomposition									
Pure composition effect	-0.0854**	-0.182***	-0.135**	-0.129***	-0.0659*	-0.0671*	-0.0449	-0.0344	-0.0347
	(0.0429)	(0.0534)	(0.0542)	(0.0470)	(0.0396)	(0.0359)	(0.0354)	(0.0339)	(0.0414)
Specification error	-0.0656	-0.0520	0.0105	0.00396	-0.0340	0.0346	0.0315	-0.0503	-0.00423

[16] This is also confirmed by our results for the standard measures of the top-end (90–50 log wage gap) and the low-end (50–10 log wage gap) gender gap in earnings, as well as for the variance of the log pay gap and the Gini coefficient (see Appendix, Table A4). The gender wage gap for 90–10, 50–10 and 90–50 differences are negative and significant, suggesting that the gender wage gap tends to narrow as we move up the wage distribution.

[17] Appendix, Table A4 also confirms that at the top-end (90-50) of the distribution, the coefficient is negative, although insignificant, while at the low-end (50-10), the coefficient of the wage gap is positive, suggesting that the wage gap in favor of men declines as we move up the distribution.

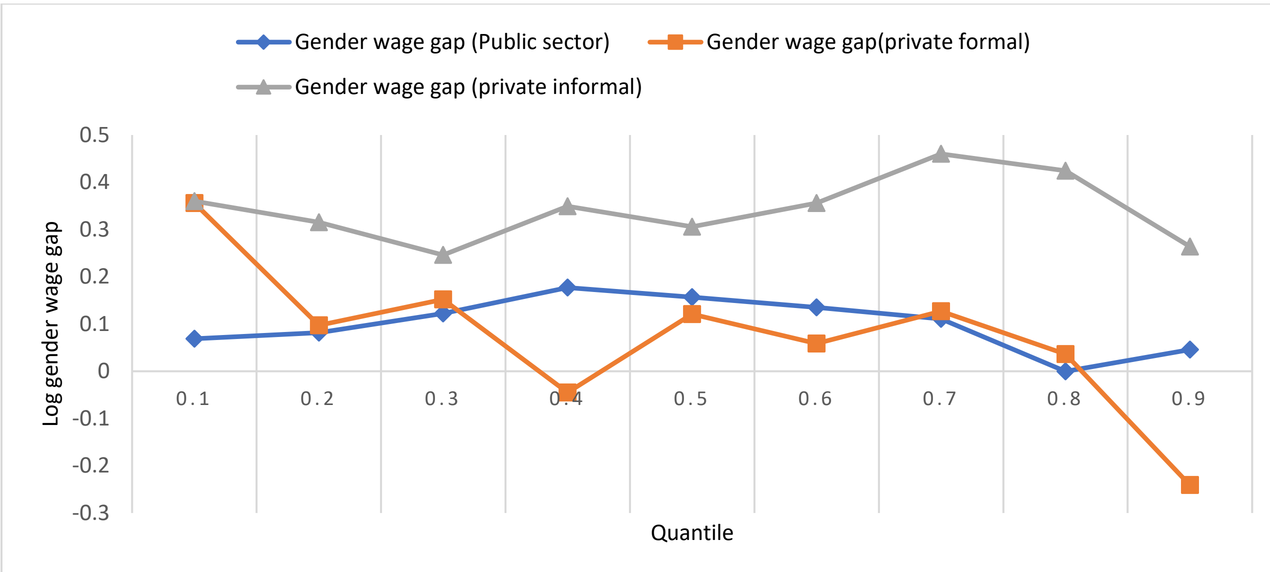
	(0.0891)	(0.0853)	(0.0793)	(0.0689)	(0.0555)	(0.0506)	(0.0485)	(0.0505)	(0.0719)
Pure structural effect	0.292***	0.373***	0.334***	0.315***	0.304***	0.209***	0.186***	0.137**	0.121
	(0.101)	(0.0910)	(0.0827)	(0.0678)	(0.0585)	(0.0553)	(0.0557)	(0.0598)	(0.0787)
Reweighting error	-0.0719	-0.0574	-0.0878	-0.0130	-0.0472	-0.0418	-0.0624*	-0.0529	-0.0357
	(0.0490)	(0.0564)	(0.0544)	(0.0456)	(0.0379)	(0.0360)	(0.0364)	(0.0384)	(0.0470)
Private Formal Sector									
Log Male earnings (M)	9.007***	9.312***	9.641***	9.652***	9.953***	10.11***	10.35***	10.61***	11.05***
	(0.0610)	(0.0528)	(0.0402)	(0.0428)	(0.0440)	(0.0470)	(0.0544)	(0.0746)	(0.0878)
Log Female earnings (F)	8.652***	9.214***	9.489***	9.697***	9.832***	10.06***	10.22***	10.57***	11.30***
	(0.128)	(0.0705)	(0.0623)	(0.0552)	(0.0535)	(0.0552)	(0.0674)	(0.114)	(0.179)
Gender Pay Gap	0.356**	0.0973	0.152**	-0.0452	0.121*	0.0589	0.127	0.0360	-0.241
	(0.142)	(0.0881)	(0.0742)	(0.0698)	(0.0692)	(0.0725)	(0.0866)	(0.136)	(0.199)
Reweighting decomposition									
Counterfactual (C)	9.059***	9.257***	9.588***	9.817***	9.992***	10.19***	10.42***	10.76***	11.21***
	(0.0467)	(0.0544)	(0.0463)	(0.0456)	(0.0497)	(0.0508)	(0.0556)	(0.0849)	(0.0948)
Total composition effect (M – C)	-0.0515	0.0541	0.0536	-0.165***	-0.0386	-0.0709	-0.0757	-0.151	-0.150
	(0.0768)	(0.0758)	(0.0613)	(0.0625)	(0.0664)	(0.0693)	(0.0777)	(0.113)	(0.129)
Total structural effect (C – F)	0.407***	0.0432	0.0987	0.120*	0.160**	0.130*	0.203**	0.187	-0.0910
	(0.136)	(0.0891)	(0.0777)	(0.0716)	(0.0730)	(0.0750)	(0.0874)	(0.142)	(0.202)
RIF aggregate decomposition									
Pure composition effect	-0.0723*	-0.0685*	-0.0511	-0.0486	-0.0954**	-0.112**	-0.179***	-0.242***	-0.303***
	(0.0416)	(0.0397)	(0.0322)	(0.0370)	(0.0404)	(0.0438)	(0.0536)	(0.0761)	(0.0848)
Specification error	0.0207	0.123	0.105*	-0.116*	0.0567	0.0413	0.103	0.0908	0.152
	(0.0829)	(0.0794)	(0.0618)	(0.0614)	(0.0613)	(0.0632)	(0.0704)	(0.0985)	(0.120)
Pure structural effect	0.378***	0.0399	0.102	0.0387	0.0515	0.0541	0.0755	-0.0218	-0.249
	(0.140)	(0.101)	(0.0827)	(0.0497)	(0.0739)	(0.0745)	(0.0836)	(0.131)	(0.196)
Reweighting error	0.0292	0.00326	-0.00333	0.0811	0.108*	0.0757	0.127**	0.209**	0.158
	(0.0441)	(0.0565)	(0.0491)	(0.0763)	(0.0568)	(0.0594)	(0.0643)	(0.101)	(0.105)
Informal Sector									
Log Male earnings (M)	6.341***	7.816***	8.432***	8.764***	8.938***	9.171***	9.439***	9.721***	9.967***
	(0.0613)	(0.0678)	(0.0297)	(0.0225)	(0.0207)	(0.0208)	(0.0214)	(0.0218)	(0.0235)
Log Female earnings (F)	5.981***	7.501***	8.186***	8.415***	8.631***	8.816***	8.978***	9.296***	9.702***
	(0.0697)	(0.0957)	(0.0447)	(0.0270)	(0.0253)	(0.0251)	(0.0283)	(0.0322)	(0.0371)
Gender Pay Gap	0.360***	0.315***	0.246***	0.349***	0.306***	0.356***	0.460***	0.424***	0.264***
	(0.0928)	(0.117)	(0.0537)	(0.0352)	(0.0327)	(0.0326)	(0.0355)	(0.0389)	(0.0439)
Reweighting decomposition									
Counterfactual (C)	6.226***	7.740***	8.380***	8.707***	8.935***	9.120***	9.325***	9.676***	9.978***
	(0.0607)	(0.0862)	(0.0330)	(0.0225)	(0.0210)	(0.0206)	(0.0212)	(0.0227)	(0.0244)
Total composition effect (M – C)	0.115	0.0764	0.0521	0.0570*	0.00274	0.0513*	0.114***	0.0446	-0.0110
	(0.0863)	(0.110)	(0.0444)	(0.0318)	(0.0295)	(0.0293)	(0.0302)	(0.0315)	(0.0339)
Total structural effect (C – F)	0.245***	0.239*	0.194***	0.292***	0.304***	0.304***	0.346***	0.380***	0.275***
	(0.0924)	(0.129)	(0.0556)	(0.0351)	(0.0329)	(0.0325)	(0.0354)	(0.0394)	(0.0444)
RIF aggregate decomposition									
Pure composition effect	0.0713***	0.0687**	0.0520***	0.0459***	0.0457***	0.0502***	0.0525***	0.0496***	0.0293***
	(0.0234)	(0.0313)	(0.0171)	(0.0144)	(0.0142)	(0.0137)	(0.0130)	(0.0120)	(0.0110)
Specification error	0.0433	0.00776	1.35e-05	0.0110	-0.0430	0.00102	0.0617**	-0.00506	-0.0403
	(0.0846)	(0.106)	(0.0415)	(0.0289)	(0.0263)	(0.0262)	(0.0278)	(0.0296)	(0.0326)
Pure structural effect	0.146	0.166	0.0982	0.148***	0.161***	0.152***	0.250***	0.310***	0.235***
	(0.110)	(0.152)	(0.0614)	(0.0383)	(0.0355)	(0.0352)	(0.0388)	(0.0435)	(0.0498)
Reweighting error	0.0990	0.0732	0.0961**	0.145***	0.143***	0.152***	0.0961***	0.0700***	0.0409
	(0.0682)	(0.0998)	(0.0396)	(0.0272)	(0.0254)	(0.0246)	(0.0248)	(0.0261)	(0.0276)

Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The dependent variable is the estimated RIF at the respective decile of the log earnings. The gender wage gap is the difference between log male earnings and log female earnings. Sampling weights are not used in the estimations. Standard errors reported in parentheses are robust. The reweighting factors have been estimated using the logit model. *** p<0.01, ** p<0.05, * p<0.1.

Figure 16 shows that the pay differential across employment sectors is primarily driven by the wage structural (discrimination) effect rather than the endowment (composition) effect. However, the contribution of the structural effect varies significantly across the earnings distribution. At the lower end, the structural effect is strongest in the private formal sector (50.2 percentage), while at the higher end, it is more pronounced in the informal sector (46.2 percentage). In contrast, the endowment effect is stronger in the public sector, particularly at the lower end of the distribution. This suggests that, based on observed productivity-related endowments, the gender pay gap could decrease by 8 to 31 percentage across the distribution, with this effect being more prominent in the public sector compared to the informal sector.

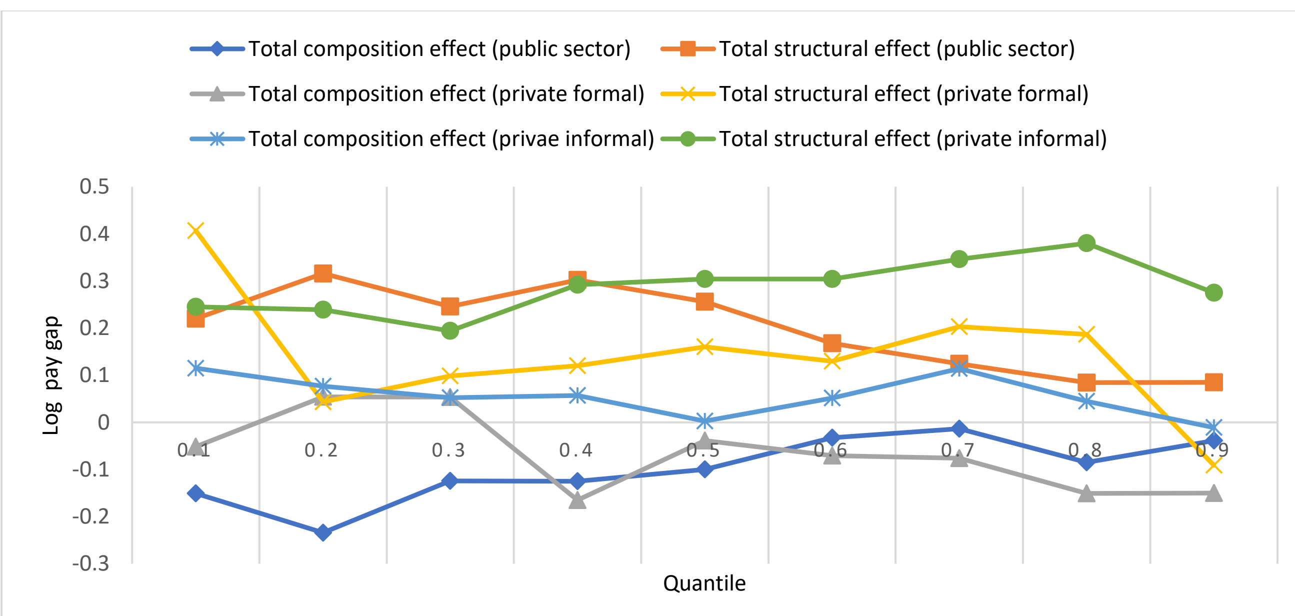
Additionally, the significant weight of the wage structural effect observed in the public sector at the top of the distribution may reflect favoritism toward men rather than direct discrimination against women. For instance, top management positions in the public sector are often tied to political appointments, which tend to favor men over women. These findings align with those of Agesa et al. (2013) and Omanyo (2021) and they suggest the presence of a "sticky-floor" effect, where the pay gap disadvantaging women is more pronounced at the lower end of the earnings distribution. The decomposition results also agree with our earlier descriptive analysis, where I found that the public sector has the smallest gender pay gap, while the private formal sector has the largest.

Figure 15: Breakdown of gender pay gap by percentiles and sectors of employment.



Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The entries are based on the reweighted RIF-Oaxaca decomposition results given in Table 19.

Figure 16: Wage structural and composition effects by sectors of employment.



Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The entries are based on the reweighted RIF-Oaxaca decomposition results given in Table 19.

6.4.8 Detailed decomposition by sectors of employment and age cohorts

To identify the most important covariates explaining gender differences in earnings and assess whether their significance varies across the earnings distribution, I turn to the detailed decomposition results. The RIF regressions underlying these results, presented in Appendix tables A1 and A2 and depicted in figures 17 and 18, reveal the key factors driving gender pay gaps and how their influence varies across the earnings spectrum. The covariates highlighted in the detailed decomposition align with those highlighted in the RIF-Oaxaca decomposition (tables 18 and 19). However, their relative importance shifts across different points of the distribution.

Based on the results in Figure 17 and Appendix Table A1, education and sectoral differences are the largest contributors to the gender pay gap through the composition effect for both younger and older workers. The contribution of education is negative and statistically significant across all deciles of the earnings distribution for both age groups. This aligns with the descriptive findings that women have higher educational attainment than men, which is well-rewarded in the labor market. This effect is more pronounced among older workers, reflecting positively on the Kenyan government's efforts to promote gender equality in education and upskilling.

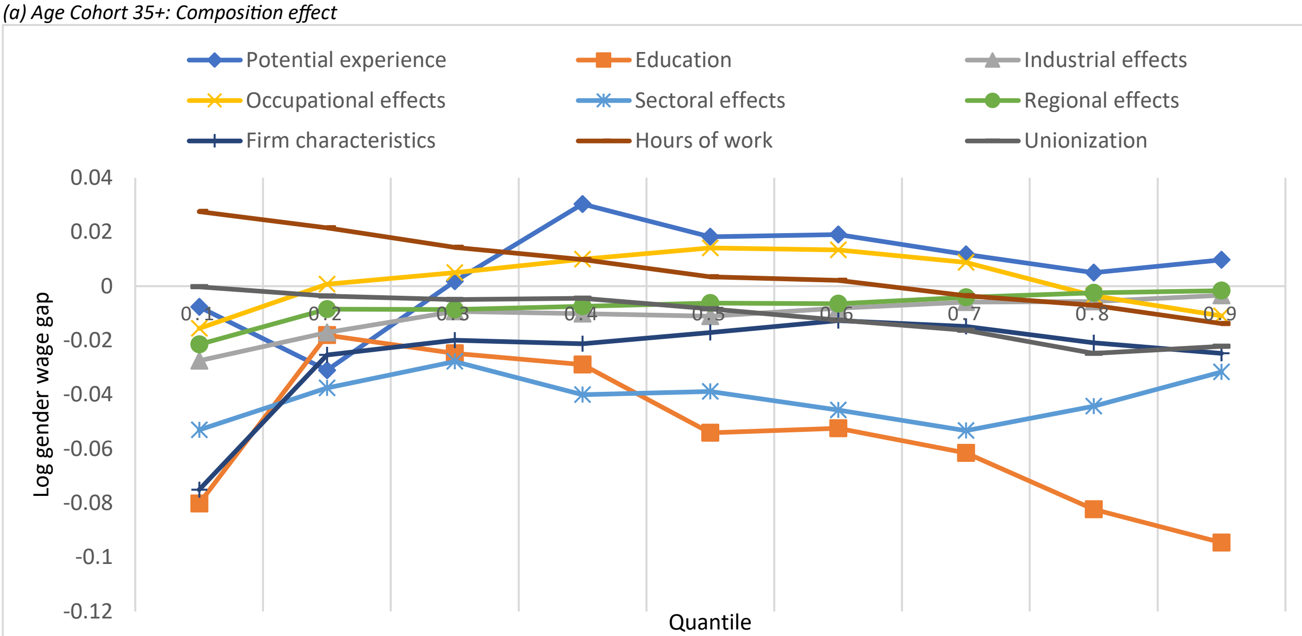
Similarly, sectoral effects consistently reduce the gender pay gap across the earnings distribution, with a more pronounced impact for older workers compared to younger ones. For older workers, gender differences in sectoral choice reduce the GPG by 3 to 6 percentage, with larger reductions at the bottom and top of the distribution. For younger workers, the reduction ranges from 1 to 3 percentage. Among older workers at the lower end of the distribution, most covariates contribute to narrowing the GPG through the composition effect, except for gender differences in hours of work, which widen the gap. This is expected, as men typically work more hours in their main occupation than women. Also, from the middle to the upper end of the earnings distribution, gender differences in potential experience and occupational distribution widen the GPG for older workers. In contrast, for younger workers, gender differences in potential experience and regional effects contribute to widening the GPG across the entire distribution. The share of the GPG attributable to differences in potential work experience is highest among younger workers, reaching around 9 percentage at the bottom decile, compared to just 3 percentage at the third decile for older workers.

Next, gender differences in firm characteristics contribute to reducing the pay gap for both younger and older workers. However, this effect diminishes as we move up the earnings distribution. For older workers, gender differences in firm size account for around 8 percentage of the pay gap reduction at the bottom decile, but this decreases to approximately 3 percentage at the top decile. Despite the declining magnitude and relative importance of firm characteristics, their impact remains economically significant.

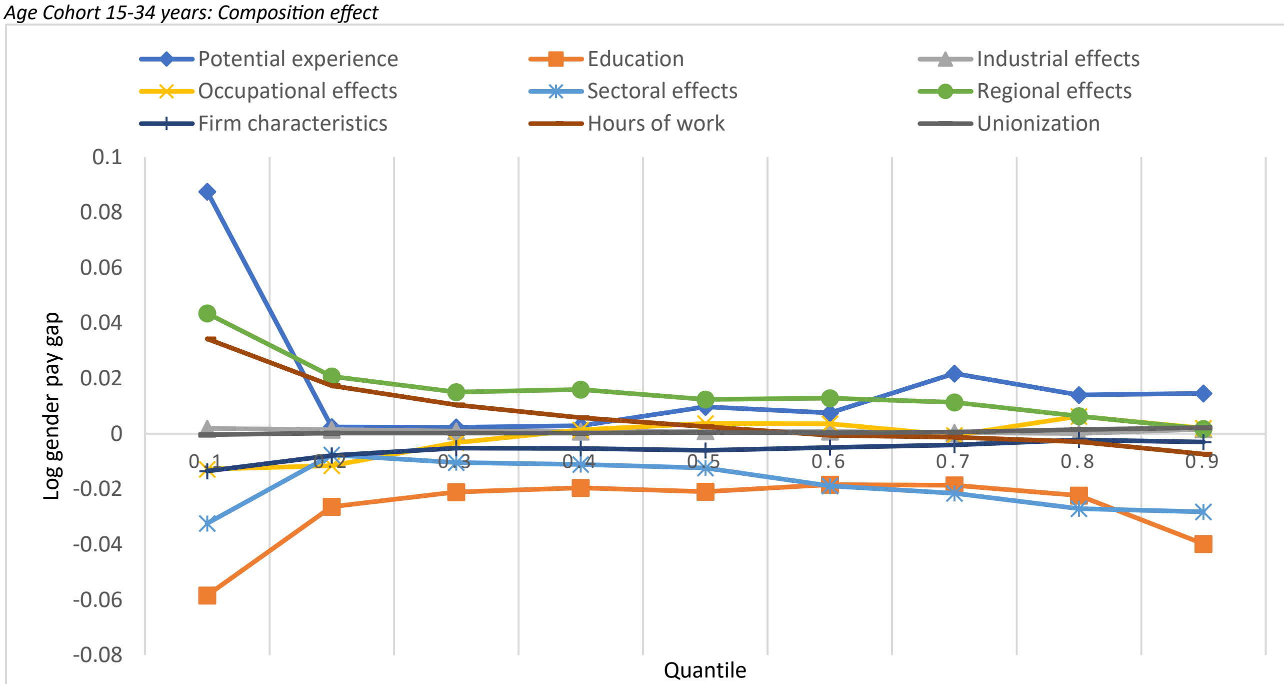
Turning to the wage structural effect (Figure 18 and Appendix Table A1), which reflects gender differences in the returns to endowments, I observe distinct patterns across age groups and earnings levels. For older workers, gender differences in the returns to potential experience increase the structural effect between the 50th and 60th percentiles, as well as at the 80th percentile. At the lower end of the distribution, gender differences in the returns to potential experience, firm characteristics, occupations, and regional effects all contribute positively to the wage structural effect, widening the gender pay gap. In the middle of the distribution, however, gender differences in the returns to hours of work, regional effects, and firm characteristics reduce the structural effect, while the returns to education increase it. At the top decile, the returns to education reduce the pay gap through the structural effect. For younger workers, the covariate contribution to the wage structural effect is most pronounced at the bottom decile. Gender differences in the returns to potential experience and sectoral choices increase the structural effect, while other covariates reduce it, implying a net effect that favors women.

Figure 17: A detailed breakdown of the composition effect by age groups.

(a) Age Cohort 35+: Composition effect



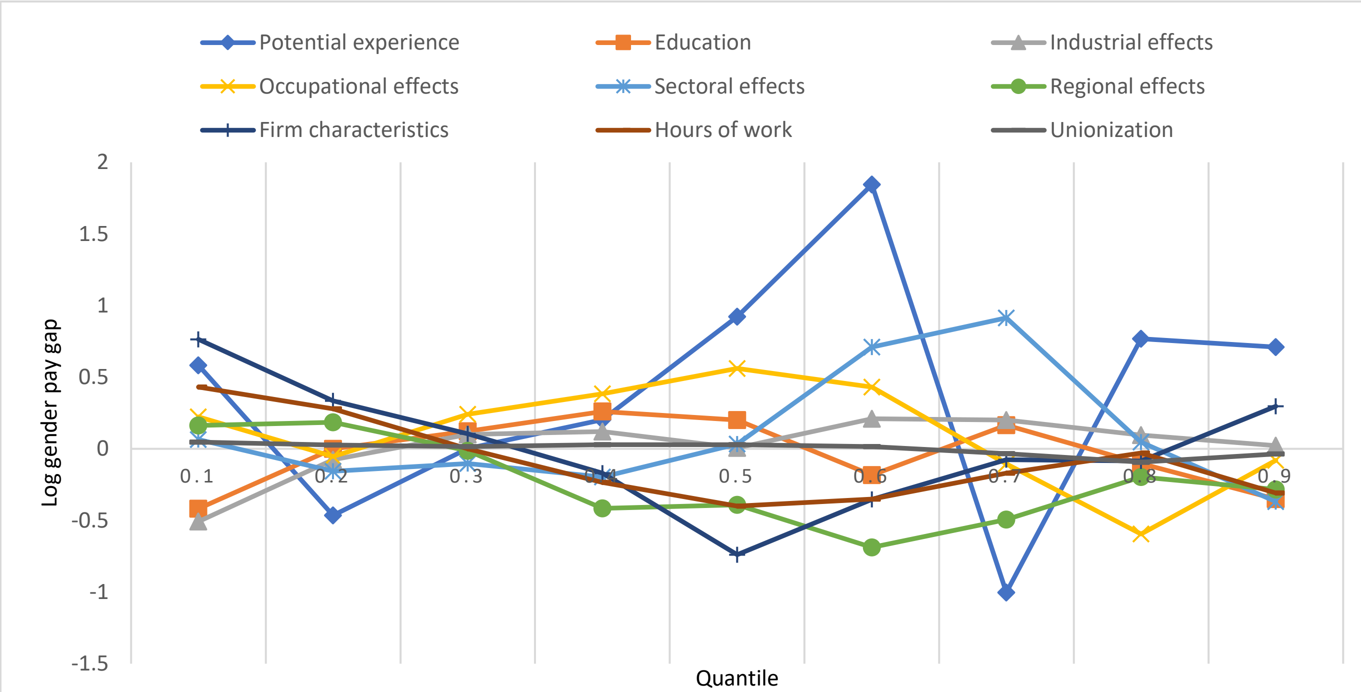
(b) Age Cohort 15-34 years: Composition effect



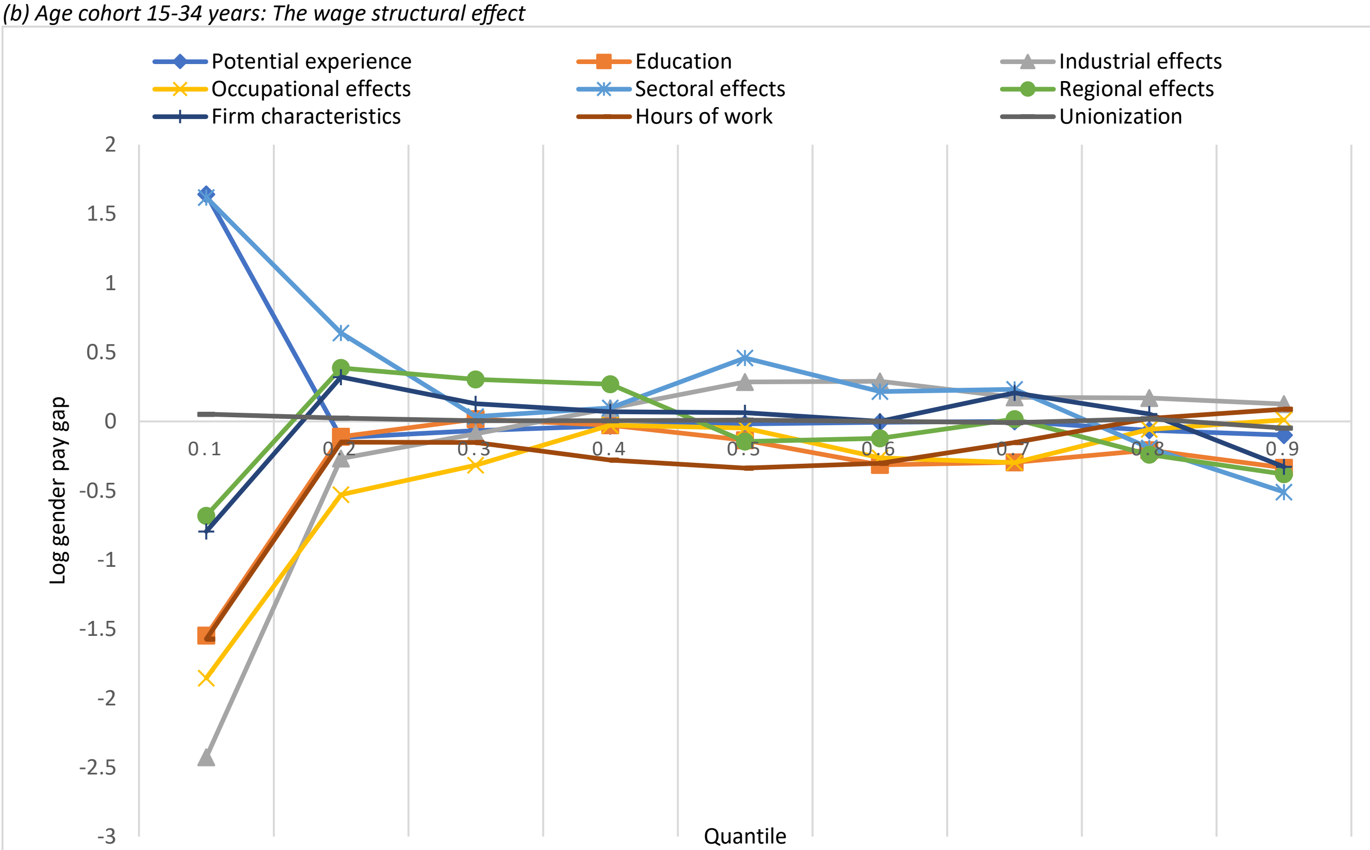
Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The entries are based on the reweighted RIF-Oaxaca decomposition results given in the Appendix, Table A1.

Figure 18: A detailed decomposition of wage structural effect by age groups

(a) Age Cohort 35+: The wage structural effect



(b) Age cohort 15-34 years: The wage structural effect



Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The entries are based on the reweighted RIF-Oaxaca decomposition results given in the Appendix, Table A1.

Figure 19 and Appendix Table A2 highlight the significant variation in how different covariates contribute to the gender pay gap through the composition effect across sectors. In both the public and private formal sectors, education has a negative and statistically significant impact on the GPG across the entire earnings distribution. This effect is stronger in the private formal sector, where gender differences in education could reduce the GPG by 8.2 to 43 percentage, depending on the decile. In the public sector, the reduction is smaller, ranging from 5.7 to 10 percentage. In stark contrast, in the informal sector, gender differences in education contribute positively to the GPG through the composition effect. This effect is most pronounced at the lower end of the distribution, where the GPG increases by approximately 3.2 percentage at the bottom decile and 1.8 percentage points at the top decile.

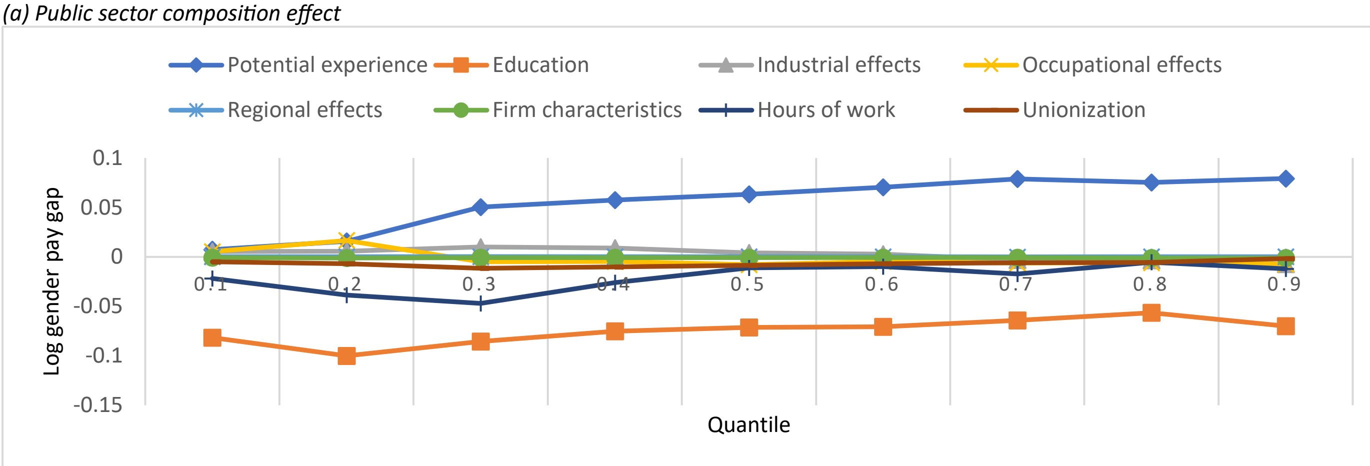
The results also indicate that gender differences in potential experience contribute positively to the gender pay gap across the earnings distribution through the composition effect. This effect is more pronounced in the public sector compared to the informal sector. Consistent with earlier findings, men tend to have more potential experience than women and they are rewarded more for it, particularly in the public sector. Additionally, at the lower deciles of the earnings distribution, gender differences in hours of work help narrow the pay gap in the public sector through the composition effect. In the private formal sector, this effect is minimal but observable at the top deciles. In contrast, in the private formal sector, all covariates except unionization contribute positively to the GPG across the distribution. This is most evident in gender differences in education, region of residence, and firm characteristics.

As regards the wage structural effect, Figure 20, and Table A2 reveal mixed contributions of covariates to the gender pay gap across sectors. In the public sector, gender differences in returns to education widen the pay gap between the 10th and 60th percentiles. However, this effect reverses at the top deciles, indicating that discrimination against women in returns to education is more prevalent among low-wage earners, while high-wage women benefit from favorable returns. In contrast, in the private formal sector, differences in returns to education reduce the GPG across the entire earnings distribution, with a stronger effect at the lower deciles. Similarly, in the public sector, gender differences in returns to industrial choice also contribute to widening the GPG, mirroring the patterns observed for education. However, in the private formal sector, the effect of gender differences in returns to industrial choice is positive across the earnings distribution, contributing to a wider GPG.

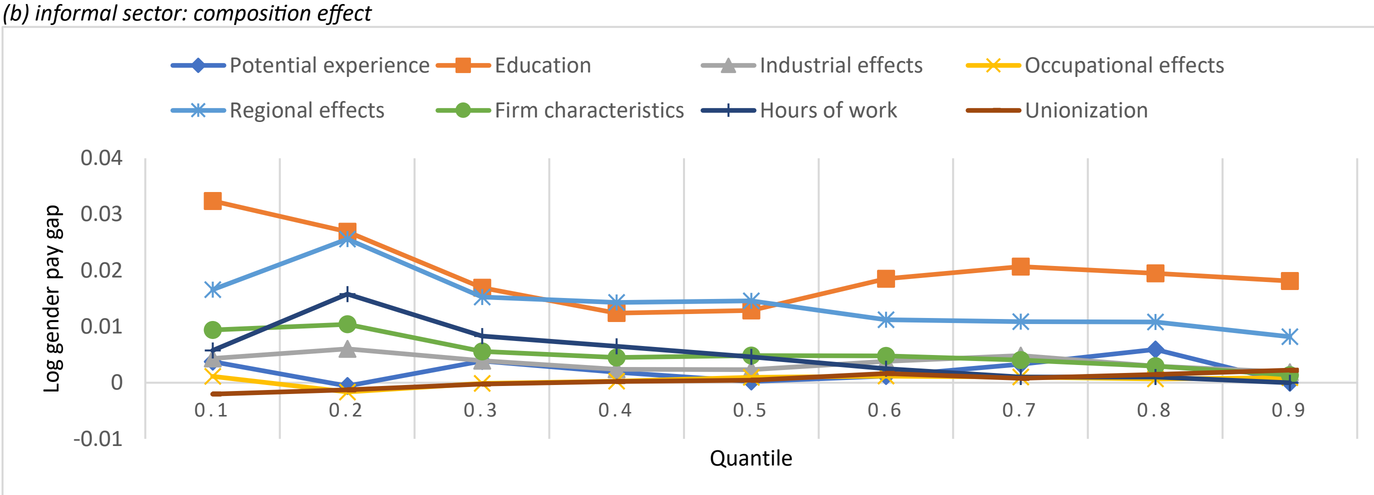
In the public sector, gender differences in returns to firm characteristics, regional effects, and hours of work reduce the GPG across the distribution through the structural effect. In the private formal sector, the effect of firm characteristics and regional residence in narrowing the GPG is more pronounced at the top deciles. In the private informal sector, the covariates' contribution to the GPG through the structural effect is most significant at the bottom deciles and remains relatively flat and close to zero from the 3rd decile upward. In this sector, returns to occupational choice, industrial choice, education, and potential experience reduce the GPG, while differences in returns to firm characteristics, hours of work, and regional residence widen it.

<u>*Figure 19:* A detailed breakdown of the composition effect by sectors of employment</u>

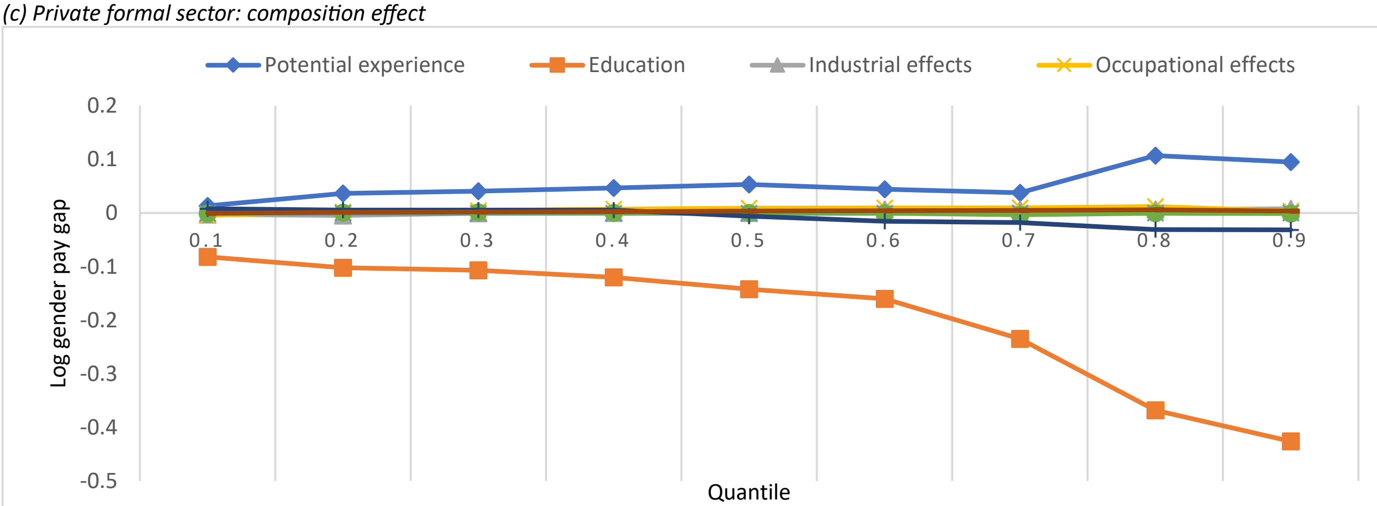
(a) Public sector composition effect



(b) informal sector: composition effect



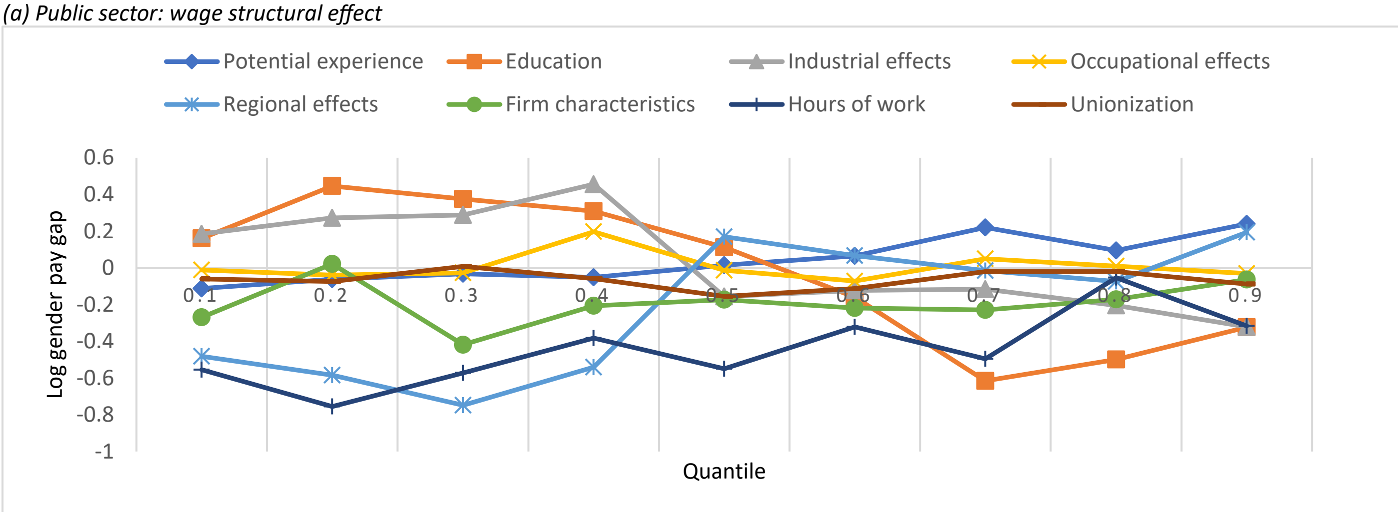
(c) Private formal sector: composition effect



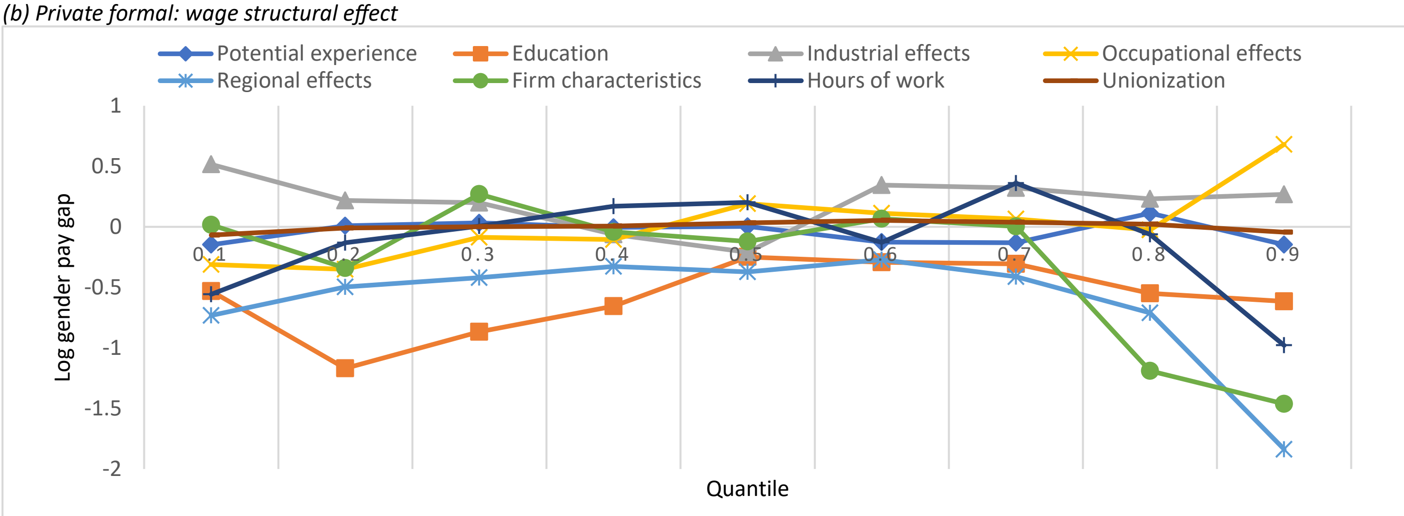
Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The entries are based on the reweighted RIF-Oaxaca decomposition results given in Table A2.

Figure 20: A detailed decomposition of the wage structural effect by sectors of employment

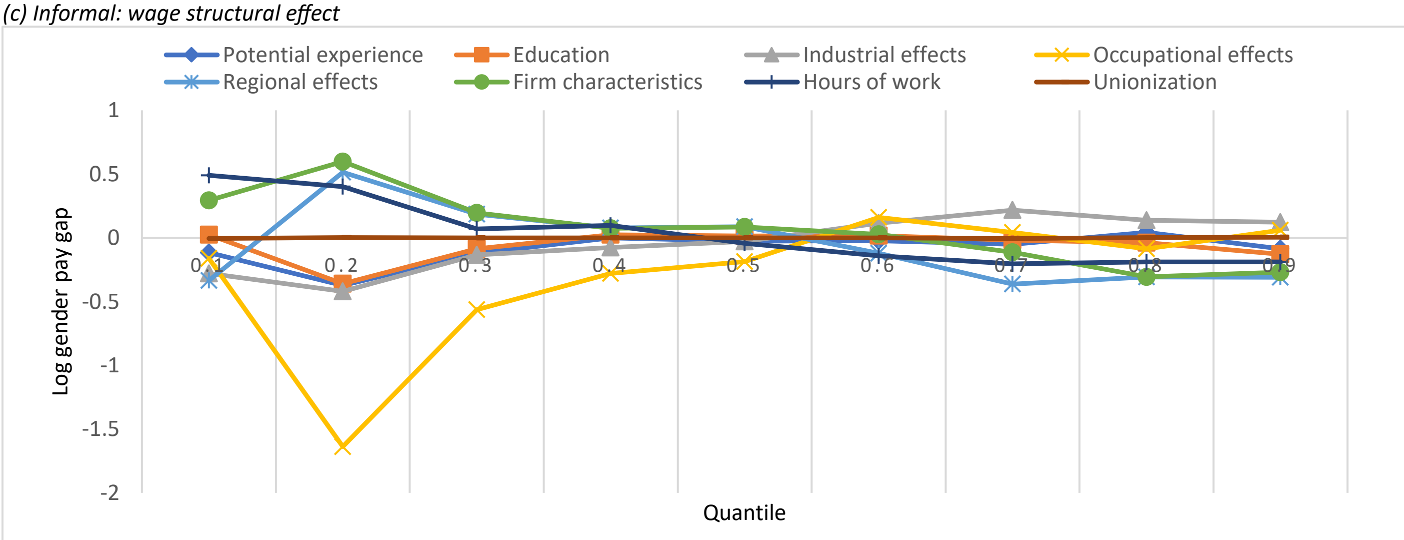
(a) Public sector: wage structural effect



(b) Private formal: wage structural effect



(c) Informal: wage structural effect



Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The entries are based on the reweighted RIF-Oaxaca decomposition results given in Table A2.

6.4.9 Discussion of the results

The gender pay gap in Kenya is deeply intertwined with the structural and institutional realities of its labor market. The decomposition results reveal systemic inequities that align with broader labor market trends, including high informality, weak enforcement of labor regulations, and gendered occupational segregation. Below, I contextualize the GPG findings within Kenya's labor dynamics to enrich the findings.

The dominance of structural effects—accounting for 70.1% to 113.4% of the GPG at aggregate mean—reflects systemic biases in wage determination that disproportionately disadvantage women. Weak enforcement of labor laws and limited collective bargaining coverage perpetuate wage discrimination. For instance, only 24% of wage employees are covered by collective agreements, leaving women vulnerable to employer discretion in wage-setting (KLMP, 2024) highlights that. The undervaluation of women's returns to education and experience mirrors broader trends of occupational crowding, where women are overrepresented in low-growth sectors like agriculture (employing 60% of informal workers) and underrepresented in high-paying industries such as mining and construction. The results further underscores the role of informality in exacerbating disparities. With 81% of non-agricultural employment being informal and 97% of agricultural workers being in informal roles, women face a "sticky floor" effect, trapped in low-productivity jobs with minimal social protection. This is most evident in the private informal sector, where the GPG peaks at 0.349 log points (41.8%). Informal sector dynamics, such as unregulated working hours and the absence of union representation (only 14% of EPZ workers are unionized), increase structural discrimination. The labor inspectors in Kenya are critically under-resourced (1 inspector per 147,000 workers), undermining efforts to enforce equal pay mandates in these sectors.

The public sector's relatively low GPG (6.4%) reflects Kenya's institutional efforts to promote gender parity through policies like affirmative action in education and public service recruitment. However, structural biases persist at higher deciles, where political appointments for top managerial roles favor men—a trend corroborated by the KLMP's observation of male-dominated leadership in county governments. The public sector's stronger unionization rates (e.g., the Kenya County Government Workers Union) and adherence to standardized pay scales mitigate disparities but fail to eliminate favoritism in promotions and benefits. In contrast, the private formal sector exhibits a GPG of 8.1%, driven by cyclical wage discrimination at lower deciles. This signals the realities in Export Processing Zones, where firms resist unionization and enforce precarious contracts. For example, EPZ workers endure long hours and casual employment, with women disproportionately relegated to low-skilled roles in apparel manufacturing. This could be linked to Kenya's pursuit of foreign investment, which prioritizes cost-cutting over equitable labor practices. The informal sector's extreme GPG (41.8%) underscores the failure of Kenya's "equal pay for equal work" policy in unregulated markets. Women in informal trade, domestic work, and agriculture lack access to social protections like the National Social Security Fund**,** which covers only 9% of the population**.** This could be potentially attributed to fiscal constraints and a lack of political will to formalize informal enterprises, leaving women's labor undervalued and unprotected.

The GPG actually widens with age, reflecting cumulative discrimination. For older workers (35+), the GPG peaks at 40% (30th percentile), driven by structural effects such as unequal returns to experience and occupational segregation. This could be due to the fact that older women are often confined to informal caregiving or subsistence farming due to limited retraining opportunities, exacerbating earnings penalties. At the same time, younger workers (15–34) face a narrower GPG (9.5%) but encounter emerging barriers, including gig economy precarity and mismatched skills. Notably, 20% of Kenyan youth are NEET (not in education, employment, or training), with women disproportionately affected by childcare responsibilities and limited access to vocational training. While education reduces the GPG through composition effects (–13% contribution), its beneficial impact is undermined by structural undervaluation. Women's higher educational attainment—50% of tertiary graduates are female—is poorly rewarded in sectors like agriculture and informal trade, where credentialism holds little sway. This could be potentially explained by Kenya's skills mismatch, where TVET programs fail to align with labor market needs, leaving women overqualified for low-skilled roles. For instance, despite 643,000 TVET enrollees in 2023, only 500–600 apprenticeships are available annually, limiting pathways to formal employment.

6.5 Chapter conclusion

Here I sought to empirically investigate the gender pay gap in Kenya's formal (public and private) and informal sectors, as well as across distinct age cohorts. The findings revealed pronounced heterogeneity in the GPG across sectors and age cohorts. In the informal sector, where 84.1% of Kenya's workforce is employed, the GPG is starkest, with women earning 41.8% less than men. This disparity is driven overwhelmingly by structural effects—systemic biases in wage determination—which account for 80.8% of the gap. Informal labor markets, characterized by weak regulatory enforcement and the absence of collective bargaining, exacerbate discrimination, particularly in male-dominated industries like manufacturing. In contrast, the public sector exhibits the smallest GPG (6.4%), attributable to standardized pay scales, stronger anti-discrimination policies, and higher unionization rates. However, even here, structural effects dominate (269.5% contribution), reflecting persistent favoritism toward men in leadership roles and political appointments. The private formal sector, while offering higher returns to education, has a GPG of 8.1%, with a pronounced "sticky floor" effect that adversely affects low-wage women. Sectoral decomposition further highlights institutional contrasts. In the public sector, gender differences in education and unionization narrow the GPG, but political patronage perpetuates ceilings for women in leadership. The private formal sector's market-driven wage-setting amplifies discrimination, while the informal sector's unregulated environment entrenches disparities through occupational crowding and unpaid care burdens. Urban residence and firm size marginally benefit women in formal sectors but fail to offset structural biases.

Age cohort analysis underscores cumulative inequities. Older women (35+) face a GPG nearly double that of younger cohorts (15–34), peaking in middle deciles. Structural effects, including undervalued returns to experience and occupational segregation, account for 200% of the gap among older workers. Younger women, despite higher educational attainment, confront barriers such as overqualification in informal roles and discrimination in male-dominated industries. While education reduces the GPG through composition effects (−13.3%), its mitigating potential is undermined by systemic undervaluation, particularly in informal sectors where credentials yield minimal returns. While education and sectoral policies have mitigated disparities at the margins, structural barriers—rooted in discriminatory wage-setting, occupational segregation, and weak enforcement—remain entrenched.

7. CEILINGS OR FLOORS? THE GENDER PAY GAP BY EDUCATION STRATIFICATION IN KENYA

7.1 Introduction

The human capital model asserts that investments in education and training—key components of human capital—correlate positively with economic returns, shaping individual earning potential (Polacheck, 2006). Supporting this premise, the European Commission (2005) identifies education as the most critical measurable factor influencing gendered earnings disparities, with higher educational attainment reducing occupational segregation between men and women. As both sexes increasingly achieve comparable levels of schooling, their convergence into similar professional roles contributes to a narrowing of the gender pay gap. This dynamic underscores how earnings differentials are primarily shaped by occupational stratification and, more fundamentally, by disparities in educational achievement. Specifically, individuals with advanced or limited education develop divergent skill sets and competencies, channeling them into distinct career pathways. Consequently, a worker's educational background not only dictates their occupational opportunities but also directly affects their earning capacity, thereby modulating the scale of gender-based pay inequality.

Kenya has instituted a comprehensive legal and policy framework to promote educational equity, enshrined in its 2010 Constitution, which mandates free and compulsory basic education. Significant strides have been made toward gender parity: girls' primary school enrollment has increased substantially, though gross enrollment rates at the secondary level remain skewed toward males. Nonetheless, female net enrollment rates have consistently exceeded those of males since 2010, a trend attributed to targeted initiatives such as the Free Primary Education and Free Day Secondary Education programs. These policies sought to universalize access and achieve full primary-to-secondary transition rates, culminating in a rise from 83.3% in 2018 to 95% by 2020 (KIPPRA, 2013; Ministry of Education, 2008; KNBS, 2021). Consequently, literacy rates now exceed regional benchmarks, with marked advancements in intermediate and advanced educational attainment among formal-sector workers. Despite these achievements, structural inequities endure, particularly in rural and marginalized regions. Furthermore, persistent socio-cultural norms—including child marriage, FGM, and early pregnancies—continue to disproportionately impede educational access for girls.

Affirmative action frameworks and gender mainstreaming strategies in Kenya have markedly enhanced women's access to tertiary education, including universities and TVET institutions. This shift is exemplified by rising female participation in STEM disciplines, signaling progress in narrowing gender divides within high-growth sectors (CUE, 2018). Anchored in Kenya's Vision 2030 and the Big Four Agenda—which position TVET as a cornerstone of economic modernization—the sector operates under the regulatory oversight of the TVET Act of 2013 and the TVET Authority, bolstered by partnerships among national agencies, county governments, and industry actors. Enrollment in TVET institutions soared to 643,000 learners by 2023, representing a 16% enrollment-to-secondary-school ratio (KNBS *Economic Survey*, 2023). Despite this growth, systemic bottlenecks—such as outdated curricula, fragmented industry-academia linkages, and limited apprenticeship opportunities (only 500–600 annually for 90,000 TVET trainees)—undermine the system's efficacy and equitable outcomes (World Bank, 2023).

Human capital disparities constitute a key determinant of Kenya's Gender Pay Gap. Although women's educational attainment has notably increased—with female secondary net enrollment rates exceeding those of males—returns on education remain stratified by gender. Highly educated women encounter a pronounced glass ceiling effect, evidenced by their underrepresentation in high-productivity sectors such as energy (17.2% in electricity/gas roles) despite occupying 50% of managerial positions (KLMP, 2024; World Bank, 2025). In contrast, low-educated women face a persistent sticky floor effect, disproportionately clustered in informal, low-paying occupations, with an 86% informal employment rate among women compared to 77% for men. Systemic inequities are further underscored by disparities in NEET rates: 24% of young women aged 15–24 remain excluded from the workforce or educational pathways, compared to 15% of their male counterparts (KLMP, 2024). This bifurcation justifies the fact that educational stratification perpetuates hierarchical pay gaps.

Recent empirical investigations into gender pay disparities, particularly those tied to educational attainment, reveal distinct patterns shaped by differences in productive characteristics and their associated economic rewards. De la Rica et al. (2008) demonstrate that among highly educated workers, wage gaps intensify at higher earnings percentiles, aligning with the glass ceiling hypothesis, whereas the disparity diminishes for less-educated individuals. Addabbo and Favaro (2011) found that low-educated Italian workers face wage gaps driven predominantly by unequal rewards, particularly at the upper end of the earnings distribution. Conversely, highly educated women exhibited superior productivity-related attributes compared to men, mitigating—though not eliminating—wage differentials. Similarly, Mussida and Picchio (2014) observed pronounced wage penalties for low-educated women, concentrated at the lower tiers of the earnings spectrum. Padayachie's (2015) South African study corroborated these findings, identifying a persistent glass ceiling for highly educated women and a "sticky floor" effect trapping low-educated workers in wage stagnation.

Notably absent from Kenya's empirical literature is a detailed analysis of the gender earnings gap disaggregated by educational attainment. This chapter seeks to address this critical gap by employing quantile regression to analyze individual covariates across the earnings distribution and then apply the Machado and Mata (2005) decomposition to compute the observed and counterfactual earnings gaps at each decile of the distribution. Here, I disentangle the pay gap into components attributable to disparities in productive characteristics and discriminatory returns to these endowments, to illuminate structural inequities. Specifically, I assess whether a *glass ceiling*[18]—systemic barriers limiting upward mobility for highly educated women—or a *sticky floor*[19] —entrapment of low-educated women in low-wage roles—predominates in Kenya's labor market. This dual focus advances scholarly debates on how educational stratification interacts with labor market dynamics to sustain gendered pay disparities.

7.2 Literature Review

Mussida and Picchio (2014) investigated educational stratification in gender wage disparities in Italy, utilizing longitudinal data taken from the European Community Household Panel (1994–2001). Their analysis applied quantile regression to model wage distributions, controlling for covariates and correcting for sample selection bias, while stratifying their sample by educational attainment (highly educated vs. low-educated workers). Building on this, they employed a decomposition technique to isolate the proportion of the wage gap attributable to differential returns to comparable characteristics across the entire earnings spectrum. Crucially, their findings underscored pronounced wage penalties for women, particularly those with lower educational qualifications. These disparities intensify when accounting for unobserved

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

heterogeneity through sample selection adjustments, notably at the lower quantiles of the wage distribution. This suggests that structural inequities—rooted in both observable and latent factors—disproportionately constrain low-educated women's earning potential, reinforcing labor market segmentation.

De la Rica et al. (2008) explored the intersection of educational attainment and gendered wage disparities in Spain, analyzing data from the European Community Household Panel. Their study employed quantile regression and panel data methodologies to assess wage differentials across the earnings distribution. Contrary to the steeply ascending gender pay gaps documented in other nations, Spain exhibited a comparatively flat trend, masking a nuanced compositional divide. For highly educated workers, the gap expanded at higher earnings percentiles, aligning with the conventional glass ceiling hypothesis. Conversely, among low-educated workers, the disparity diminished toward the upper quantiles—a phenomenon the authors labeled a "floor pattern." They theorized that this counterintuitive trend could stem from statistical discrimination by employers, particularly in sectors where less-educated women face low labor force participation rates, skewing perceptions of their productivity and reinforcing occupational segregation.

Wirba et al. (2021) analyzed gender wage inequities within Cameroon's informal economy using data from the 2010 Labor Force Employment Survey. Their findings revealed that both disparities in human capital endowments and discriminatory returns to these endowments contributed to gendered earnings gaps. Workers with elementary education earned wages 0.373 log points higher than those with a basic education, while tertiary-educated individuals commanded a 0.602 log-point premium. Notably, the returns to work experience exhibited divergent gendered patterns: incremental gains for women diminished over time, whereas men experienced a linear, positive relationship between experience and earnings. This suggests that, despite structural barriers, women in informal sectors accrued relative wage advantages with accumulated experience compared to men. Furthermore, the gender pay gap narrowed progressively from the lower to upper quantiles of the wage distribution—a trend the authors associated with a *sticky floor* dynamic, wherein women face disproportionate constraints at the lower earnings tiers. The study also identified evidence of statistical discrimination against women in low-wage informal roles, reflecting employer biases that devalue female labor even in unregulated markets.

Addabbo and Favaro (2011) investigated the interplay of gender and educational stratification in shaping wage disparities in Italy, attempting to discern whether the gender pay gap diverged between highly educated and low-educated workers and to evaluate how differences in human capital endowments versus labor market rewards contributed to these gaps. Employing quantile regression and an adaptation of the Machado and Mata (2005) decomposition framework, the study analyzed data taken from the European Community Household Panel to estimate predicted wage gaps across the female earnings distribution. Their results revealed stark contrasts: for low-educated workers, the wage gap stemmed predominantly from unequal returns to comparable characteristics (e.g., education, experience), particularly at the upper quantiles of the distribution. In contrast, highly educated women exhibited superior productivity-related attributes relative to men, such as advanced qualifications or skills, which partially offset—though did not eliminate—earnings disparities.

7.3 Empirical Strategy: Machado and Mata Decomposition

The Oaxaca-Blinder decomposition method, a seminal framework for analyzing average gender earnings disparities, disentangles the gap into two components: (1) the *explained* portion, and (2) the *unexplained* portion (Blinder, 1973; Oaxaca, 1973). However, a persistent critique of this approach is its focus on mean differences, which obscures heterogeneity across the earnings spectrum. Empirical evidence demonstrates that the gender pay gap is not uniform but varies markedly along the wage distribution, with distinct patterns at the lower, median, and upper quantiles (Albrecht et al., 2003; Arulampalam et al., 2007; De la Rica et al., 2008). To address this limitation, Machado and Mata (2005) pioneered an innovative framework integrating quantile regression with bootstrap resampling. This method constructs counterfactual wage distributions, enabling researchers to isolate how disparities in characteristics versus returns evolve across the entire earnings continuum (Heinze, 2010).

Quantile regression, pioneered by Koenker and Bassett (1978), extends traditional regression analysis by estimating conditional quantiles rather than means, thereby facilitating examination across the entire distribution of a response variable without requiring normality assumptions. Unlike OLS regression, which focuses on average effects by shifting the conditional mean through covariates, quantile regression employs a linear framework to model how covariates influence specific quantiles (Koenker & Hallock, 2001). While OLS isolates mean shifts, quantile regression reveals the differential impact of covariates across the distribution spectrum, offering subtle insights into marginal effects at various quantiles—from lower to upper tails—rather than merely 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:

$$Q_\theta\left(lnWij \middle| g_{ij}, X_i, Z_i\right) = g_{ij}\alpha_\theta + X_i\beta_\theta + Z_i\delta_\theta + \mu_{\theta ij}, \tag{7.1}$$

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

$$lnW_{ij} = g_{ij}\alpha_\theta + X_i\beta_\theta + Z_i\delta_\theta + \mu_{\theta ij} \quad for\ g = m, f; i = 1,2, \ldots \ldots, N; j = 1,2, \ldots \ldots, M \tag{7.2}$$

Here $\mu_{\theta ij}$ satisfies $Q_\theta\left(lnWij \middle| g_{ij}, X_i, Z_i\right) = 0$. 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 (7.2) can be estimated separately for males and females:

$$lnW_{ij} = X_{ij,g}\beta_g(\theta) + Z_{ij,g}\delta_g(\theta) + \mu_{\theta ij,g} \quad for\ g = m, f; i = 1,2,, N_g; j = 1,2, \ldots \ldots, M \tag{7.3}$$

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[20] framework proposed by Koenker and Bassett (1978). Specifically, they are obtained by solving the following minimization problem:

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

$$Z_{ij,g}\delta_g(\theta)| + \textstyle\sum_{i.lnW_{ij,g} < X_{ij,g}\beta_g(\theta) + Z_{ij,g}\delta_g(\theta)} (1-\theta) |\, lnW_{ij,g} - X_{ij,g}\beta_g(\theta) - Z_{ij,g}\delta_g(\theta)| \Big] \tag{7.4}$$

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

The estimated coefficients from quantile regression, denoted as $\hat{\beta}(\theta)$[21] 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 (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 that it only considers the mean of the covariate distributions, ignoring variations in higher moments.

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 $\left(\hat{\beta}_g\theta, \hat{\delta}_g\theta\right)$, 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

[21] I 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.

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.

4. Decompose the gender pay gap. Lastly, decompose the difference between the θth quantile of the male and female wage distributions into two components[22]:

$$X_m\hat{\beta}_m(\theta) - X_f\hat{\beta}_f(\theta) = \left(X_m - X_f\right)\hat{\beta}_m(\theta) + X_f\left(\hat{\beta}_m(\theta) - \hat{\beta}_f(\theta)\right) + residual \quad (7.5)$$

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 errors: simulation errors, sampling errors, and specification errors arising from the linear quantile regression model. Here, I 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 (7.5) 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 productivity characteristics).

7.4 Results and Discussion.

7.4.1 Mean characteristics by gender

Table 20 presents summary statistics for covariates used to model earnings distributions among wage-employed workers in Kenya, stratified by gender and educational attainment. The variables, aligned with Mincerian wage equation frameworks, encompass factors capturing human capital (potential experience, job tenure), labor market (region of residence), job characteristics (occupation, employment contract type), firm attributes (sector, firm size), and demographic traits (marital status). While occupation may introduce endogeneity due to its potential correlation with unobserved productivity traits, it is retained in the model to proxy for latent heterogeneity. Consequently, its coefficient is interpreted descriptively rather than causally, to avoid structural claims about their direct impact on earnings.

[22] The decomposition of differences in wage distributions is applied using the Stata command rqdeco (see Melly, 2007). Melly (2006) shows that this procedure is numerically identical to the Machado and 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.

Table 20: Summary statistics of the worker's covariates by gender and education

	Low educated men		Low educated women		Highly educated men		Highly educated women	
	Mean	**SD**	**mean**	**SD**	**mean**	**SD**	**mean**	**SD**
Gross monthly earnings	8.566	1.394	8.213	1.385	10.145	1.267	10.0289	1.0958
Age (years)	35.757	11.428	34.767	10.733	36.954	9.971	35.924	10.0902
Potential experience	14.00934	11.0743	13.0249	10.373	14.966	9.951	13.942	10.0618
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	9.0292	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								
Occ1	0.0128	0.112	0.00984	0.0987	0.0510	0.220	0.0404	0.197
Occ2	0.0320	0.176	0.0451	0.207	0.439	0.496	0.603	0.489
Occ3	0.0268	0.161	0.0127	0.112	0.111	0.314	0.0571	0.232
Occ4	0.0049	0.0702	0.0115	0.107	0.0127	0.112	0.0585	0.234
Occ5	0.141	0.3489	0.190	0.392	0.155	0.362	0.1506	0.357
Occ6	0.246	0.431	0.377	0.484	0.0421	0.201	0.0292	0.168
Occ7	0.238	0.426	0.0457	0.209	0.0919	0.289	0.0167	0.128
Occ8	0.144	0.351	0.0191	0.136	0.0702	0.255	0.00976	0.0983
Occ9	0.151	0.358	0.288	0.453	0.0255	0.157	0.0334	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	0.0204	0.141	0.0179	0.132	0.0395	0.195	0.0599	0.237
100 and above	0.0703	0.255	0.0602	0.238	0.157	0.364	0.125	0.331
Employment sector								
Public sector	0.0741	0.261	0.066	0.248	0.527	0.499	0.624	0.484
Private formal	0.0834	0.276	0.0735	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	0.0373	0.189	0.0237	0.152	0.243	0.429	0.277	0.448
N	**3427**		**1726**		**783**		**717**	

Source: Author's calculations (2024) based on KCHS (2021). Note: SD-Standard deviation

Highly educated men command a significant earnings premium, with average gross monthly wages of 10.145 log points, surpassing both highly educated women (10.0289 log points) and low-educated workers. Notably, low-educated women occupy the lowest earnings tier at 8.213 log points. Demographic disparities further underscore labor market stratification: highly educated individuals are older on average, with men aged 37 compared to 36 years for both highly educated and low-educated women. Similarly, highly educated men have greater potential work experience (15 years) than highly educated women (14 years) and low-educated women (13 years). Marital status disparities persist across educational tiers, with men more likely to be married—65.1% of low-educated men versus 51.3% of low-educated women, and 78.5% of highly educated men versus 65.1% of highly educated women. To account for the tenure's influence on wages, the analysis incorporates a continuous measure of years in current occupation. Here, highly educated women marginally outperform their male counterparts and low-educated workers, averaging 9 years of tenure, suggesting nuanced intersections of education and retention in moderating wage outcomes.

Labor market dynamics reveal stark disparities in work hours and geographic distribution by educational attainment. Low-educated men report the highest weekly working hours in their primary occupations, exceeding those of low-educated women and highly educated workers of both genders. Residential patterns further reflect this stratification: highly educated workers predominantly reside in urban areas, most likely driven by access to formal, skill-intensive employment, while low-educated workers cluster in rural regions. Household size also diverges, with highly educated workers—particularly women—exhibiting smaller households compared to their low-educated counterparts. This aligns with demographic behaviors suggesting that highly educated women prioritize quality over quantity in child-rearing, opting for fewer children with greater investments in education and health. Notably, household size serves as an exclusion restriction in the selection equation to address potential endogeneity, but it is omitted from wage distribution specifications to isolate its role in labor market participation decisions.

Educational attainment shapes stark disparities in employment sectors: highly educated workers are disproportionately concentrated in public sector roles, with 52.7% of men and 62.4% of women in such positions. Conversely, low-educated workers are predominantly clustered in the informal sector, comprising 84.2% of men and 86% of women. To model earnings, occupational categories are incorporated as dummy variables, reflecting their critical role in explaining wage differentials. Empirical literature underscores the relevance of these variables, as occupational segregation—particularly the clustering of women in lower-paying roles—has been identified as a structural determinant of the gender pay gap (Bayard et al., 2003; Addabbo & Favaro, 2011; Orraca et al., 2016; Ismail et al., 2017). The descriptives reveal pronounced occupational stratification by educational attainment. Low-educated workers are predominantly employed in blue-collar, craft, and elementary occupations, reflecting limited access to skilled roles. In contrast, highly educated women are disproportionately represented in professional positions, with 60.3% working in such roles compared to 43.9% of highly educated men.

Firm size further delineates disparities: among low-educated workers, 15.8% of men and 13.3% of women work in small firms, 2% of both genders in medium firms, and 7% of men and 6% of women in large firms. For highly educated workers, women slightly outnumber men in small firms (52% vs. 44%), while men are marginally more prevalent in large firms. Union membership underscores systemic inequities: 27.7% of highly educated women and 24.3% of highly educated men belong to labor unions, compared to just 3.7% of low-educated men and 2.4% of low-educated women. These patterns highlight the precarious employment conditions and diminished labor protections characterizing low-educated workers' roles, reinforcing their vulnerability in the labor market.

7.4.2 Mincer OLS earnings estimations

Building on the methodological flexibility noted in the descriptive statistics section—where covariates are modeled to account for their heterogeneous association with wage density functions—the analysis confirms that these variables exert varying marginal effects at different quantiles. This heterogeneity is captured in tables 21 and 22, which report selectivity bias-corrected coefficients for men and women, accounting for potential non-random selection in wage employment for both highly educated and low-educated workers. The results highlight how occupational, demographic, and firm-level factors differentially shape earnings disparities at lower, median, and upper quantiles.

The Mincer earnings framework attributes a substantial share of wage variation to human capital accumulation, particularly formal education, and labor market experience. To operationalize human capital beyond formal schooling, I construct a proxy for *potential labor market experience* by deducting 6 years (accounting for pre-primary education) and formal education duration from an individual's actual age (Age-6-S). This yields an estimate of years spent in the workforce post-schooling, which is incorporated into the wage equation as a continuous variable for potential experience. Following conventional practice, potential experience is modeled in quadratic form (experience and experience squared) to reflect its concave relationship with earnings: initial gains in wages diminish over time as returns to experience taper.

Coefficients positively correlated with wages typically confer a *wage premium*—indicating higher earnings relative to the reference group. Potential experience exerts a significant positive association with wages across all educational tiers, though its association is strongest at the lower quantiles of the wage distribution. This reflects the multiple advantages of accumulated skills and tenure for older workers. However, the concave relationship—captured by the diminishing marginal returns of experience—reveals an inverted U-shaped trajectory: earnings rise with age until plateauing and declining as workers approach retirement, particularly among highly educated cohorts.

Marital status exerts divergent association with earnings across educational and gender strata in Kenya. For low-educated men, marriage correlates with a pronounced wage premium at the median and upper percentiles of the earnings distribution, potentially reflecting employer biases that equate marital status with workplace stability and commitment. Conversely, highly educated women benefit from marital status at the lower and median wage tiers, suggesting that their advanced credentials partially offset gendered stereotypes. However, low-educated women face a wage penalty at median percentiles, albeit statistically insignificant—a trend most likely rooted in socio-cultural dynamics. Married women often bear disproportionate responsibilities for unpaid domestic labor (the *"second shift"*), constraining their labor market participation and reinforcing perceptions of reduced availability. And Kenya's elevated fertility rate may amplify employer discrimination, as marriage is perceived to signal higher risks of career interruptions, further penalizing women in informal or low-skilled roles.

Table 21: Coefficient estimates by education stratification- male model

	Highly educated			Low educated		
	25th	50th	75th	25th	50th	75th
Potential experience	0.0859**	0.0627***	0.0600***	0.0842***	0.0345***	0.0346***
	(0.0398)	(0.0219)	(0.0142)	(0.0175)	(0.00757)	(0.00718)
Square of experience	-0.00135*	-0.000975**	-0.000906***	-0.00125***	-0.000425***	-0.000552***
	(0.000690)	(0.000414)	(0.000335)	(0.000391)	(0.000151)	(0.000133)
Married	0.235	0.163	0.176	0.214	0.221***	0.259***
	(0.178)	(0.145)	(0.111)	(0.167)	(0.0452)	(0.0563)
Hours of work	-0.00133	0.000676	-0.00411**	0.0140***	0.00875***	0.00526***
	(0.00314)	(0.00229)	(0.00168)	(0.00260)	(0.000872)	(0.00114)
Tenure	0.0324***	0.0210***	0.0153**	-0.00645	0.00468*	0.00816***
	(0.00911)	(0.00426)	(0.00668)	(0.00618)	(0.00245)	(0.00259)
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	-0.828***	-0.726***	-0.795***	-	-	-
	(0.140)	(0.105)	(0.254)			
Bachelor's degree	-0.0857	-0.267**	-0.365	-	-	-
	(0.175)	(0.118)	(0.264)			

Public sector	0.104	0.156	0.0506	0.118	0.236**	0.374***
	(0.136)	(0.0997)	(0.100)	(0.159)	(0.116)	(0.0915)
Private informal	-0.598***	-0.454***	-0.414***	-0.443***	-0.268***	-0.294***
	(0.154)	(0.142)	(0.119)	(0.134)	(0.0600)	(0.0663)
Occupations						
occ1	0.471	0.552**	0.854***	0.806***	0.781***	0.495***
	(0.309)	(0.237)	(0.308)	(0.174)	(0.124)	(0.129)
occ2	0.181	0.451**	0.701**	0.0904	0.267***	0.337***
	(0.337)	(0.221)	(0.274)	(0.143)	(0.0726)	(0.118)
occ3	0.275	0.572***	1.007***	0.215	0.447***	0.536***
	(0.355)	(0.208)	(0.232)	(0.182)	(0.0727)	(0.131)
occ4	-0.0328	0.353*	0.634	0.559*	0.579***	0.528***
	(0.406)	(0.207)	(0.410)	(0.326)	(0.120)	(0.188)
occ5	0.288	0.320	0.611**	-0.0816	0.173***	0.227***
	(0.312)	(0.221)	(0.255)	(0.125)	(0.0482)	(0.0523)
occ6	-0.794	0.0847	0.505*	-0.516***	0.0273	0.0239
	(0.648)	(0.391)	(0.270)	(0.177)	(0.0351)	(0.0406)
occ7	0.185	0.291	0.612**	-0.0953	0.330***	0.478***
	(0.375)	(0.253)	(0.243)	(0.147)	(0.0538)	(0.0558)
occ8	0.531	0.559**	0.793***	-0.202	0.409***	0.528***
	(0.339)	(0.223)	(0.254)	(0.272)	(0.0617)	(0.0701)
urban	-0.0845	0.0815	0.106	-0.255	-0.0980	-0.0430
	(0.184)	(0.129)	(0.107)	(0.188)	(0.0703)	(0.0896)
Firm size						
10-49 employees	0.131	-0.0444	-0.0563	0.320***	0.244***	0.165***
	(0.129)	(0.0957)	(0.0998)	(0.0881)	(0.0532)	(0.0479)
50-99 employees	0.472	0.235	0.272	0.378**	0.252*	0.102
	(0.323)	(0.205)	(0.225)	(0.180)	(0.141)	(0.0658)
100 and above	0.277	0.203**	0.223*	0.587***	0.493***	0.408***
	(0.196)	(0.0908)	(0.131)	(0.104)	(0.0525)	(0.0645)
Labor union	0.235	0.220**	0.185**	0.102	0.218***	0.0784*
	(0.162)	(0.0865)	(0.0885)	(0.206)	(0.0660)	(0.0459)
Mills ratio	1.196*	0.519	0.406	1.324***	0.689***	0.499***
	(0.681)	(0.466)	(0.402)	(0.448)	(0.148)	(0.188)
Constant	8.262***	9.093***	9.675***	6.377***	7.589***	8.323***
	(0.693)	(0.488)	(0.546)	(0.516)	(0.206)	(0.185)
Observations		783			3,427	
Pseudo R^2	0.333	0.3170.372		0.108	0.127	0.160

Source: Author's calculations (2024) based on KCHS (2021). Bootstrap standard errors with 20 replications in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Note: Occ1, Occ2, Occ3, Occ4, Occ5, Occ6, Occ7, and Occ8 are the defined occupations in Table 2 where Occ1 is "Legislators, Administrators, and Managers" and Occ8 is "Plant and machine operators and assemblers".

Weekly working hours in primary occupations significantly boost earnings for both low-educated men and women across the wage distribution, underscoring the labor market's reliance on intensive work schedules for lower-skilled roles. Tenure—years in the current occupation—uniformly enhances wages for highly educated men, reflecting returns to specialized expertise. For low-educated men, tenure's positive association is confined to median and upper quantiles, suggesting limited upward mobility without formal credentials. Among women, only low-educated workers at the upper tail experience significant tenure-related gains, highlighting constrained opportunities for career progression. Sectoral disparities further stratify earnings: public sector employment correlates with a wage premium relative to the private formal sector (reference category), while informal sector roles are linked to reduced earnings, exacerbating precarity. Geographic inequities compound these patterns, with urban residents facing pronounced wage penalties. Low-educated men in urban areas experience consistent earnings disadvantages across the distribution, while low-educated women endure disproportionate setbacks at the lower quantiles, reflecting intersecting vulnerabilities of education, gender, and spatial marginalization.

Occupational categories exhibit varied associations with earnings across gender and educational strata. Relative to elementary occupations (the reference group), roles such as *legislators, administrators, and managers* correlate with elevated earnings for both highly and low-educated men and women, underscoring the premium placed on leadership and managerial skills. Similarly, *professionals, technicians, and associate professionals* command higher wages at the median and upper tiers of the earnings distribution, reflecting returns to specialized expertise. Clerical roles significantly benefit low-educated workers of both genders uniformly across the wage spectrum, offering a stable earnings advantage despite limited educational attainment. Sector-specific disparities emerge starkly in agriculture, forestry, and fishery. Highly educated men in this sector experience wage gains at the upper quartile (75th percentile), while low-educated men see modest increases at the lower quartile (25th percentile). Conversely, low-educated women face systemic penalties in this sector across all wage levels, highlighting entrenched gender biases in agrarian labor markets. Male-dominated occupations—such as *craft and trade-related work* and *plant/machine operation*—confer wage premiums for low-educated men and women at median and upper quartiles, though these gains remain stratified by gender, with men benefiting disproportionately.

Table 22: Coefficient estimates by education stratification- Female model

	Highly educated			Low educated		
	25th	50th	75th	25th	50th	75th
Potential experience	0.103***	0.0892***	0.0296	0.0956***	0.0354**	0.0415**
	(0.0254)	(0.0175)	(0.0196)	(0.0244)	(0.0144)	(0.0174)
Square of experience	-0.00157***	-0.00156***	-0.000247	-0.00158***	-0.000597**	-0.00705***
	(0.000556)	(0.000286)	(0.000540)	(0.000451)	(0.000247)	(0.000217)
Married	0.352***	0.326**	0.0903	0.0523	-0.0266	0.0847
	(0.136)	(0.129)	(0.144)	(0.222)	(0.127)	(0.129)
Hours of work	0.00503	0.00643*	-1.16e-05	0.0169***	0.00909***	0.00517***
	(0.00312)	(0.00358)	(0.00326)	(0.00253)	(0.00136)	(0.00169)
Tenure	0.0112	0.00935	0.00545	-0.00458	0.00408	0.00973***
	(0.00681)	(0.00896)	(0.00571)	(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	-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	0.379*	0.193*	0.230
	(0.0918)	(0.0713)	(0.120)	(0.201)	(0.102)	(0.144)
Private informal sector	-0.775***	-0.704***	-0.627***	-0.375**	-0.370***	-0.252***
	(0.160)	(0.149)	(0.183)	(0.148)	(0.105)	(0.0876)
Occupations						
occ1	0.620**	0.475**	0.433**	-0.0155	0.465	0.950**
	(0.298)	(0.205)	(0.188)	(0.299)	(0.392)	(0.391)
occ2	-0.0258	-0.00844	0.238	-0.299	-0.0678	0.220
	(0.260)	(0.222)	(0.174)	(0.225)	(0.163)	(0.157)
occ3	0.485	0.391	0.408*	0.279	0.531***	0.352**
	(0.346)	(0.240)	(0.231)	(0.375)	(0.169)	(0.175)
occ4	0.0395	0.0145	0.377	0.465*	0.622**	0.621***
	(0.278)	(0.246)	(0.250)	(0.260)	(0.298)	(0.180)
occ5	0.287	0.250	0.480**	-0.295***	0.000971	0.120*
	(0.276)	(0.213)	(0.213)	(0.113)	(0.0547)	(0.0617)
occ6	-0.265	-0.412	0.115	-0.898***	-0.310***	-0.181***
	(0.411)	(0.298)	(0.358)	(0.141)	(0.0649)	(0.0547)
occ7	0.205	-0.0451	-0.147	0.104	0.215***	0.225**
	(0.286)	(0.312)	(0.387)	(0.165)	(0.0829)	(0.102)
occ8	0.326	0.304	0.226	0.110	0.276**	0.160
	(0.348)	(0.314)	(0.301)	(0.252)	(0.118)	(0.134)
Urban	0.0344	0.0656	0.105	-0.0579	0.174	0.0604
	(0.122)	(0.112)	(0.0910)	(0.153)	(0.112)	(0.113)
Firm size						
10-49 employees	0.0663	0.0769	0.0617	0.376***	0.243**	0.329***
	(0.108)	(0.0922)	(0.0891)	(0.133)	(0.101)	(0.0759)
50-99 employees	0.0634	0.190	0.349**	0.600**	0.595***	0.622***
	(0.213)	(0.158)	(0.137)	(0.250)	(0.211)	(0.120)
100 and above	0.161	0.228*	0.0941	0.666***	0.489***	0.402***
	(0.137)	(0.136)	(0.191)	(0.149)	(0.104)	(0.0761)

Labor union	0.519***	0.499***	0.240**	0.244	0.259	0.377*
	(0.0916)	(0.0708)	(0.0985)	(0.563)	(0.160)	(0.196)
Mill's ratio	1.440***	0.981**	0.0471	0.783*	0.182	0.332
	(0.540)	(0.449)	(0.361)	(0.436)	(0.253)	(0.331)
Constant	7.955***	8.618***	10.87***	6.061***	7.845***	8.002***
	(0.681)	(0.431)	(0.536)	(0.875)	(0.487)	(0.608)
Observations		717			1,726	
Pseudo R^2	0.337	0.320	0.272	0.169	0.141	0.188

Source: Author's calculations (2024) based on KCHS (2021). Bootstrap standard errors with 20 replications in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Note: Occ1, Occ2, Occ3, Occ4, Occ5, Occ6, Occ7, and Occ8 are the defined occupations in Table 2 where Occ1 is "Legislators, Administrators, and Managers" and Occ8 is "Plant and machine operators and assemblers".

Employment in medium to large firms (10+ employees) correlates with elevated earnings, particularly for low-educated men and women, reflecting the wage premiums tied to formalized employment structures. Labor union membership further amplifies earnings across genders, with highly educated women experiencing uniform gains throughout the wage distribution, low-educated women securing pronounced benefits at the 75th percentile, and both low- and highly educated men accruing advantages at median and upper quantiles. These findings underscore the potent bargaining influence of Kenyan unions, resonating with earlier studies by Butcher and Rouse (2001) and Ntuli (2007), which emphasized unions' role in mitigating wage suppression.

Next, the inverse Mills ratio—a measure of selection bias derived from the exclusion restriction of household size—is positive and significant for low-educated men across all wage tiers and for highly educated women at lower to median percentiles, as well as low-educated women at the distribution's base. This indicates pronounced selection effects: women with larger households face compounded burdens from unpaid domestic labor (the *"second shift"*), constraining their labor market participation, while men in similar contexts may prioritize wage employment to fulfill breadwinning expectations.

7.4.4 Gender pay gap by education across the distribution.

Now, I will decompose the gender pay gap for low- and highly educated workers in Kenya into two components: (1) disparities attributable to differences in observable characteristics and (2) disparities stemming from unequal returns to those characteristics, often interpreted as discrimination. Table 23 outlines the results of a quantile decomposition analysis needed to dissect the gender pay gap among low-educated workers in Kenya. The table is structured as follows: The first column quantifies the unconditional earnings disparity between men and women at specific quantiles of their wage distributions. The second column isolates the portion of the GPG attributable to gender differences in observable productivity-related characteristics. It represents the wage gap that would persist *if women possessed identical labor market traits as men* but retained the existing female wage structure.

The third column captures the residual disparity stemming from unequal returns to comparable characteristics—often interpreted as discrimination or institutional bias. Derived by comparing women's actual wage distribution with a *counterfactual distribution* where women retain their own traits but are remunerated under the male wage structure, it reflects systemic undervaluation of female labor. The counterfactual distribution simulates earnings outcomes under a male remuneration framework while preserving women's observable characteristics.

Table 23: Gender Pay Gap for low-educated workers.

Quantile	Observed gender pay gap	Characteristics	Coefficients	Counterfactual
.10	0.288*	-0.223**	0.511***	0
	(0.156)	(0.103)	(0.171)	(0.115)
.20	0.223**	-0.0645	0.288***	0.223**
	(0.0892)	(0.0463)	(0.0777)	(0.102)
.30	0.329***	0	0.329***	0
	(0.0712)	(0.0226)	(0.0730)	(0.0374)
.40	0.405***	0.0870	0.318***	-0.182***
	(0.0476)	(0.0727)	(0.0867)	(0.0601)
.50	0.336***	0.154***	0.182***	-0.154***
	(0.0216)	(0.0336)	(0.0401)	(0.0458)
.60	0.375***	0.134***	0.241***	-0.182***
	(0.0621)	(0.0209)	(0.0615)	(0.0351)
.70	0.511***	0.223***	0.288***	-0.203***
	(0.0179)	(0.0296)	(0.0344)	(0.0436)
.80	0.470***	0.182***	0.288***	-0.223***
	(0.0462)	(0.0270)	(0.0388)	(0.0347)
.90	0.288***	0.134*	0.154**	-0.182***
	(0.0596)	(0.0686)	(0.0459)	(0.0368)

Source: Author's calculations (2024) based on KCHS-2021 data. Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Standard errors produced via bootstrapping using 100 replications.

The gender pay gap among low-educated workers in Kenya exhibits a non-monotonic pattern across the earnings distribution, revealing stark inequities at specific quantiles. The observed pay disparity peaks at the 70th percentile (66.7%) and reaches its nadir at the 20th percentile (25%). A closer examination of deciles tells us that the gap rises steadily from the 2nd to the 4th decile, climbing from 25% to 49.9%. It then moderates slightly at the median before escalating to its zenith at the 70th percentile, followed by a sharp decline at the 90th percentile

(25.6%). Notably, women positioned above the 20th percentile face the most pronounced disadvantages, as the GPG widens significantly in these mid-to-upper earnings tiers, underscoring systemic barriers to equitable remuneration despite incremental wage gains.

The gender pay gap among low-educated workers in Kenya exhibits a pronounced upward trajectory toward the upper quantiles of the earnings distribution (Figure 21b), peaking at the 70th percentile before narrowing sharply at the 90th percentile. This contraction at the top may reflect the influence of Kenya's minimum wage policies, which disproportionately benefit unionized workers in formal sectors. While the GPG demonstrates a non-linear progression—rising from the 2nd to 4th deciles, stabilizing at the median, then escalating to its apex—the persistence of a *sticky floor* effect at the bottom deciles underscores systemic barriers for low-educated women in entry-tier roles. These findings partially diverge from Padayachie (2015), who reported widening gaps at the upper quantiles for low-educated workers but align with Ntuli (2007) and Mussida and Picchio (2014), whose work similarly identifies entrenched disadvantages at the distribution's base.

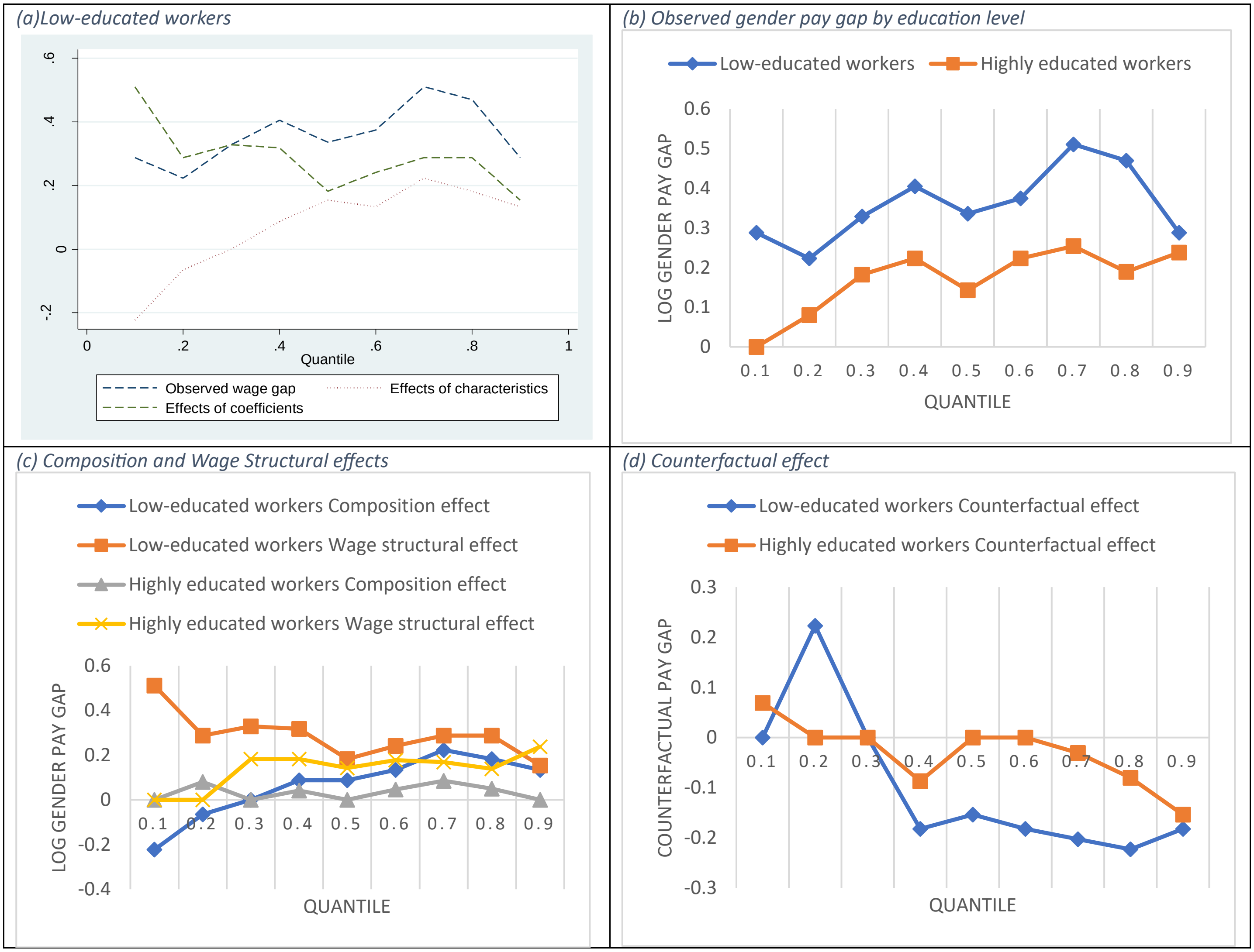
Decomposition results (Table 23, Column 2; Figure 21c) indicate that even if low-educated women possessed identical observable characteristics to men, significant earnings penalties would persist across most quantiles, except at the 20th percentile. Here, women's marginally superior productivity endowments reduce the GPG by 25%. However, across the earnings distribution, the penalty remains substantial, peaking at the 70th percentile and reinforcing the role of institutional bias in perpetuating inequities. These results mirror Mussida and Picchio's (2014) conclusion that low-educated women face compounding disadvantages, particularly in mid-to-upper earnings tiers, where labor market dynamics exacerbate the gendered valuation of human capital.

The unexplained component of the gender pay gap—captured by disparities in returns to comparable characteristics (Table 23, Column 3; Figure 21c)—is uniformly positive and statistically significant across the earnings distribution. This suggests systemic devaluation of women's human capital, as men's productivity-related attributes command disproportionately higher rewards. The discrimination-driven GPG is most severe at the lower quantiles (67% earnings penalty), where low-wage women endure compounded disadvantages due to both observable and unobserved factors, including selectivity bias from non-random labor market participation (e.g., caregiving-driven attrition). Notably, the GPG narrows at the upper quantiles

(16%), a trend potentially tied to Kenya's robust minimum wage policies and collective bargaining frameworks that elevate earnings for unionized formal-sector workers. These findings align with Padayachie (2015), who similarly documented entrenched wage discrimination against low-educated women in South Africa, particularly in informal and low-skilled roles.

The counterfactual analysis (Figure 21d) discloses a systemic undervaluation of women's productivity-related characteristics in Kenya's labor market. With the exception of the 20th percentile, the counterfactual pay gap—simulating a scenario where low-educated women retain their current traits but are compensated under the male wage structure—is *negative* across the earnings distribution. This negative gap means that, under such conditions, the wage disparity would reverse, favoring women, with reductions ranging from 0.154 log points (16%) to 0.223 log points (25%). In practical terms, aligning remuneration for women's existing characteristics (e.g., experience) with the rewards granted to men would substantially elevate women's wages, narrowing the gender pay gap at nearly all quantiles.

Figure 21: Decomposition of gender pay gap by education level.



Source: Author's calculations (2024) based on KCHS-2021 data. Bootstrapping using 100 replications.

The results for highly educated workers (Table 24) reveal a pronounced gender pay gap that escalates non-linearly across the earnings distribution, underscoring the pervasive "glass ceiling" effect (Figure 21b). This phenomenon reflects systemic barriers faced by highly educated women in high-wage roles, most likely driven by vertical occupational segregation—where women encounter limited upward mobility into senior positions despite comparable qualifications. The GPG widens progressively from the 10th percentile (8.3%) to the 40th percentile (25%), moderates slightly at the median (50th percentile, 15.3%), and peaks at the 70th percentile (28.9%).

While the gap temporarily narrows at the 80th percentile (20.8%), it resurges at the uppermost quantile (90th percentile, 26.9%), suggesting persistent inequities at the highest earnings tiers.

Critically, the GPG at median and upper quantiles consistently exceeds disparities at the distribution's base, signaling that as highly educated women ascend toward higher earnings brackets, they come up against increasing resistance to wage parity. This pattern aligns with Padayachie's (2015) findings in South Africa, which similarly identified significant wage gaps for highly educated women at upper quantiles, reinforcing the global prevalence of glass ceilings in skill-intensive labor markets. The results underscore how institutional and cultural barriers—such as gendered leadership biases and unequal access to promotions—combine to stifle women's earnings potential, even among those with advanced credentials.

Table 24: The gender pay gap (in log points) for highly educated workers.

Quantile	Observed GPG	Characteristics	Coefficients	Counterfactual
.1	0	0	0	0.0690
	(0.101)	(0)	(0.101)	(0.104)
.2	0.0800	0.0800	0	0
	(0.125)	(0.104)	(0.112)	(0.0904)
.3	0.182*	0	0.182	0
	(0.102)	(0.0976)	(0.115)	(0.0713)
.4	0.223**	0.0408	0.182*	-0.0870
	(0.0999)	(0.0917)	(0.0941)	(0.102)
.5	0.143*	0	0.143**	0
	(0.0849)	(0.0758)	(0.0669)	(0.0627)
.6	0.223***	0.0460	0.177***	0
	(0.0679)	(0.0635)	(0.0639)	(0.0445)
.7	0.254***	0.0852	0.169***	-0.0305
	(0.0640)	(0.0539)	(0.0544)	(0.0436)
.8	0.189***	0.0506	0.139***	-0.0800
	(0.0481)	(0.0374)	(0.0418)	(0.0487)
.9	0.238***	0	0.238***	-0.154***
	(0.0675)	(0.0131)	(0.0655)	(0.0510)

Source: Author's calculations (2024) based on KCHS-2021 data. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Standard errors produced through bootstrapping using 100 replications.

Even if highly educated men and women possessed identical observable characteristics (Table 24, Column 2; Figure 21c), women would still incur wage penalties of 4.7% to 8.9%, though these disparities lack statistical significance across the distribution. This suggests that compositional differences in human capital or occupational roles play a limited role in explaining the gender pay gap among highly educated workers. The *unexplained* GPG component—driven by discriminatory returns to equivalent characteristics (Table 24, Column 3; Figure 21c)—reveals systemic inequities. From the 4th decile onward, the gap becomes statistically significant, rising sharply from 14.9% at the 40th percentile to 26.9% at the 90th percentile. This stark divergence underscores how men's productivity-related attributes are disproportionately rewarded, while women's identical endowments are systematically undervalued. The widening gap at upper quantiles highlights a *glass ceiling* effect, where highly educated women face compounding barriers to wage parity as they ascend the earnings hierarchy. The unexplained GPG dominates, indicating that institutional biases—not differences in observable traits—perpetuate wage disparities. This aligns with global studies attributing such gaps to gendered valuation of labor (Blau & Kahn, 2017). Also, the findings corroborate Padayachie's (2015) analysis of South African labor markets, which similarly identified pronounced upper-quantile GPGs among highly educated workers.

The counterfactual analysis (Figure 21d) reveals a striking inversion of the gender pay gap for highly educated workers at the upper quantiles of Kenya's earnings distribution. Here, the GPG becomes *negative*, indicating that if highly educated women retained their current characteristics but were compensated under the male wage structure, their earnings would surpass men's, particularly among top earners. This reversal is most pronounced at the 90th percentile, where the gap shifts by 16.7% in women's favor. Such a scenario underscores the systemic undervaluation of women's human capital under existing wage structures. For high-wage women, equitable remuneration aligned with male earnings frameworks would not only bridge the GPG but invert it, highlighting how institutional biases in pay-setting disproportionately penalize women's productivity-related traits.

The negative counterfactual gap exposes entrenched inequities in how identical skills and qualifications are rewarded by gender, even among high earners. Mandating pay parity in high-skilled sectors—particularly through transparent salary bands and anti-discrimination audits—could mitigate these biases. By simulating a counterfactual wage structure, the analysis isolates the role of discriminatory practices in perpetuating wage disparities, reinforcing calls for institutional reforms in Kenya's formal labor markets.

The decomposition of Kenya's gender pay gap by educational stratification reveals stark disparities when further disaggregated across age cohorts and employment sectors (Table A6 and Table A7). For low-educated workers, younger women (15–34 years) face pronounced wage penalties across most quantiles, with observed gaps peaking at the 10th percentile (53.7%) and remaining elevated at the median (34%). This aligns with the *sticky floor* phenomenon, where entry-tier roles in informal sectors—dominated by younger, low-educated women—are characterized by exploitative wages and minimal labor protections. However, older low-educated women (35+ years) endure even larger gaps at upper quantiles (e.g., 74.2% at the 70th percentile), driven predominantly by *wage structural effects* (discriminatory returns to characteristics). This suggests that prolonged exposure to informal labor markets exacerbates cumulative disadvantages, as older women remain trapped in low-productivity roles with stagnant wages.

In contrast, highly educated women exhibit widening GPGs with age. While younger cohorts (15–34 years) experience moderate gaps (e.g., 22.8% at the median), older women (35+) confront severe disparities, particularly at upper quantiles (61.1% at the 90th percentile). This reflects a *glass ceiling* intensifying over careers, as older, highly educated women face systemic barriers to senior roles and wage growth. The dominance of *wage structural effects* (e.g., 53% at the 90th percentile for older women) underscores how discriminatory remuneration practices persist even among experienced professionals, negating potential gains from accumulated human capital.

Sectoral stratification reveals stark contrasts. For low-educated workers, the informal sector—employing 86% of women—exhibits higher observed GPGs (e.g., 42.9% at the median) compared to the formal sector (3.1%). The informal sector's *wage structural effects* dominate (e.g., 37.9% at the median), highlighting systemic devaluation of women's labor in unregulated markets. Even when low-educated women possess comparable characteristics to men, informal employment structures—marked by weak enforcement of minimum wages and limited unionization—perpetuate exploitation.

Among highly educated workers, the formal sector paradoxically sustains significant GPGs (38.8% at the median), driven largely by *wage structural effects* (24.4%). This aligns with vertical occupational segregation in formal sectors, where women are underrepresented in leadership roles despite comparable credentials. However, the informal sector's GPGs for highly educated women are even more severe (84.6% at the 90th percentile), reflecting the precarity of high-skilled informal roles (e.g., gig economy jobs) where algorithmic pay-setting and exclusion from labor protections amplify discrimination.

7.4.6 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 systemic undervaluation of their productivity characteristics and institutional barriers embedded in Kenya's labor market.

The results identify a "glass ceiling" effect for low-educated women, where the pay gap widens at higher earnings quantiles (70^{th} and 80^{th}). This aligns with the reality that Kenya's large informal economy—which employs 81% of non-agricultural workers—disproportionately traps low-educated women in precarious, low-productivity sectors such as retail, domestic work, and small-scale agriculture. Informal employment, characterized by minimal regulation and limited unionization, exacerbates wage discrimination. Women in these sectors often lack bargaining power, as collective agreements cover only 3.7% of total employment. Furthermore, the weak labor inspections and employer non-compliance with reinstatement orders, institutionalize exploitative practices. These factors explain the finding that the unexplained pay gap (attributed to discrimination) is highest at the lower earnings quantiles. Even when low-educated women possess comparable productivity characteristics to men, their concentration in informal roles—where wages are neither standardized nor protected—results in systemic undervaluation of their labor.

TVET programs while expanding, suffer from fragmented curricula and limited industry linkages. This mismatch between skills training and labor market demands most likely depresses the productivity returns for low-educated workers. For women, who constitute 86% of informal workers, this skills gap is compounded by societal norms that restrict their mobility and access to resources. Consequently, their "better productive characteristics" are insufficient to overcome structural barriers, leading to persistent earnings penalties.

Highly educated women face a pronounced "glass ceiling" at the upper quantiles of the earnings distribution, a trend contextualized through Kenya's gendered labor market dynamics. Despite progress in educational attainment—with women occupying 50% of managerial positions—vertical occupational segregation persists. This could be attributed to discriminatory promotion practices and cultural biases that channel women into lower-paying roles, even within formal sectors like education and public administration. For instance, while the education sector has the highest collective bargaining coverage (44%), gender disparities in leadership roles and wage negotiations undermine equitable outcomes. The finding that the unexplained pay gap peaks at the 70th percentile reflects these institutional biases, where women's advancement into high-wage positions is hindered by unequal returns on their qualifications.

Additionally, Kenya's labor laws, though progressive on paper, are inconsistently enforced. For example, maternity leave coverage remains low (6.3% of mothers), and paternity leave uptake is negligible, reinforcing gendered care burdens that limit women's career progression. And the brain drain of skilled workers—particularly in health and education—intensifies competition for formal jobs, creating environments where discriminatory practices thrive. Highly educated women, though better positioned to negotiate wages, confront systemic undervaluation of their productivity characteristics, as evidenced by the finding's emphasis on the "unexplained" pay gap driven by discriminatory remuneration.

Next, the findings tell us that low-educated women possess productivity characteristics that could theoretically reduce the pay gap, yet institutional failures negate this potential. For instance, according to KNBS *Economic Survey* (2023), 47% of Kenyan firms have female ownership, yet women-led enterprises are often confined to low-growth sectors with limited access to credit. Similarly, while TVET reforms seek to bridge skills gaps, the dominance of theoretical training over practical exposure limits the employability of graduates, especially women. This disconnect is reflected in our counterfactual analysis, which shows that low-educated women's earnings would rise significantly if their characteristics were remunerated at male rates. However, the weak labor inspections and informality reveal why this remains hypothetical: without enforceable wage standards, women's productivity gains are eroded by structural inequities.

For highly educated workers, Kenya's digital economy offers additional insights. While the Fourth Industrial Revolution has created opportunities in sectors like ICT and business process outsourcing, platform workers—many of whom are women—are classified as independent contractors and excluded from labor protection. The finding of widening pay gaps at higher quantiles aligns with this reality, as algorithmic management and precarious contracts in the gig economy exacerbate wage discrimination. Despite their advanced skills, women in digital roles face opaque pay structures and limited union representation, perpetuating the "unexplained" earnings gap.

7.5 Chapter conclusion

Here, I sought to investigate the interplay between educational stratification and the gender pay gap in Kenya. Employing a robust methodological framework, the analysis applied quantile regression and the Machado and Mata (2005) decomposition technique on data from the 2021 KCHS. The findings reveal stark contrasts in the GPG dynamics between low- and highly educated workers. For low-educated women, the GPG exhibits a "sticky floor" pattern, with the largest disparities observed at the lower quantiles of the earnings distribution. At the 10th percentile, women earn 28.8% less than men, a gap primarily driven by systemic undervaluation of their productivity-related characteristics. Decomposition results indicate that approximately 67% of this disparity stems from discriminatory returns to identical traits rather than differences in observable endowments. Even when low-educated women possess comparable qualifications and labor market traits, their concentration in informal, low-productivity sectors—where wages are unregulated and unionization rates are minimal—exacerbates earnings penalties. The counterfactual analysis underscores this inequity: aligning women's remuneration with male wage structures could reverse the GPG by up to 25%, highlighting the transformative potential of equitable pay frameworks.

For highly educated women, the GPG intensifies at the upper quantiles, revealing a pronounced "glass ceiling" effect. At the 70th percentile, women face a 28.9% earnings deficit relative to men, remaining stark at the 90th percentile (26.9%). This pattern reflects vertical occupational segregation, where women encounter barriers to ascending into leadership roles despite possessing comparable credentials. Strikingly, the decomposition attributes a larger portion of the gap at upper quantiles to discriminatory returns, underscoring institutional biases in how skills and experience are rewarded. The counterfactual analysis further illuminates this dynamic: under a male remuneration structure, highly educated women's earnings would surpass men's at the 90th percentile, demonstrating systemic devaluation of their human capital in high-wage roles. The intersection of age, education, and sectoral stratification elucidates the multifaceted nature of Kenya's GPG. While low-educated women face entrenched *sticky floors* exacerbated by informality and age-related precarity, highly educated women confront escalating *glass ceilings* in both formal and informal sectors.

These findings resonate with global literature on gendered labor market inequities while contextualizing Kenya's unique structural challenges. The persistence of a sticky floor for low-educated women aligns with studies in Cameroon and South Africa, where informal sector precarity and weak labor protections entrench wage disparities. Similarly, the glass ceiling for highly educated women mirrors trends observed in European and South African labor markets, where cultural biases and promotion barriers stifle upward mobility. However, Kenya's dual burden of a shrinking formal sector and rapid informalization amplifies these inequities, particularly for women navigating intersecting vulnerabilities of education, gender, and spatial marginalization. In conclusion, the findings presented here mean that educational attainment alone is insufficient to dismantle gendered wage disparities in Kenya. While education equips women with human capital, structural and institutional biases persistently undervalue their contributions across the earnings spectrum.

8. WHY WOMEN EARN LESS: THE ROLE OF OCCUPATIONAL SEGREGATION IN KENYA'S GENDER PAY GAP

8.1 Introduction

Occupational segregation —defined as a situation where individuals are assigned to specific occupations based on characteristics unrelated to their productivity (Liu et al., 2004)—remains a persistent structural feature of global labor markets, with well-documented consequences for wage disparities. Female-dominated occupations systematically offer lower remuneration compared to male-dominated roles, perpetuating gendered earnings inequities (Bettio & Verashchagina, 2009; Levanon et al., 2009) [23]. Empirical studies suggest a gradual, albeit slow, erosion of both occupational segregation and the gender pay gap, driven in part by rising educational attainment among women (Blau & Kahn, 2017; Weichselbaumer & Winter-Ebmer, 2005; Goldin, 2008). Enhanced female skill acquisition not only narrows wage differentials but also aligns with the diffusion of egalitarian gender norms and equity-focused policies, which further mitigate occupational divides. However, progress is neither linear nor universal; cross-national analyses reveal heterogeneous trends, with stagnation or reversals in some contexts (*see* Rubery, 2008; Bettio & Verashchagina, 2009; Stainback & Tomaskovic-Devey, 2012).

Globally, women's participation in formal sector employment has shown steady progress, with their share in modern wage occupations rising from 35% to 41% between 1990 and 2018. At the same time, the proportion of women serving as household breadwinners in low-paying roles declined from 59% to 46% (ILO, 2018). Despite these gains, systemic inequities endure. Women remain underrepresented in formal occupations—which typically offer job security, social protections, competitive wages, and safer working conditions—with only 44% of women employed in such roles compared to 66% of men, reflecting a persistent 22% gender employment gap. Even when performing comparable tasks with equivalent education, women earn less than their male counterparts. This disparity is compounded by structural barriers, including the disproportionate burden of unpaid caregiving and domestic labor, alongside inadequate

[23] It is essential to distinguish occupational segregation from occupational structure, which relates to the overall distribution of workers across occupations. Disparities in occupational structures between men and women do not necessarily indicate labor market discrimination. However, if women face barriers that impede their access to certain occupations or if their choices are constrained due to lower returns on their productivity-related attributes within those occupations, then divergent occupational structures can be regarded as manifestations of discrimination (Ehrenberg & Smith, 2012).

compensation for family-related responsibilities, which curtail women's labor market participation and career advancement (ILO, 2018).

In Sub-Saharan Africa, the HIV/AIDS pandemic disproportionately affected single-parent households, particularly those headed by widowed women who assumed sole responsibility for childcare and family survival (Egbuna, 2001). This crisis forced many women into precarious, low-wage occupations—often with minimal labor productivity—as immediate financial needs eclipsed opportunities for skill-matched or higher-paying roles. Concurrently, systemic underrepresentation of women in labor policy decision-making spheres perpetuates exclusion from shaping frameworks that govern wages, workplace rights, and employment equity (Flabbi, 2011). Compounding these challenges, deeply entrenched patriarchal norms and conservative cultural practices have historically restricted women's occupational mobility (Dan, 2010). Societal expectations often channel women into roles deemed "gender-appropriate," such as caregiving or informal trade—sectors characterized by lower wages and limited upward mobility—while discouraging participation in higher-paying, male-dominated fields. Together, these dynamics reinforce a cycle of labor market segregation, where structural inequities and cultural biases intersect to constrain women's economic agency.

In Kenya, women's employment remains concentrated in care-intensive sectors, including agriculture, education, health and social work, wholesale and retail trade, domestic services, and allied service industries. Conversely, men are disproportionately represented in traditionally male-dominated sectors such as mining and quarrying (87.2%), utilities (77.2%), and manufacturing (77.1%) (KNBS *Economics Survey*, 2023). And men are more likely to secure permanent employment contracts compared to women. Despite progress in women's educational attainment, economic participation, and formal employment opportunities, a persistent gender pay gap underscores systemic inequities in the labor market. Occupational segregation further highlights these disparities. Women constitute a marginally higher proportion of professionals (10.9% vs. 8.4%), technical and associate professionals (15.5% vs. 10%), service and sales workers (22.3% vs. 13%), and elementary occupations (34.2% vs. 32.9%). In contrast, men dominate roles as plant and machine operators and craft-related workers. Happily, however, gender parity is observed in formal and informal wage employment: women comprise 46.2% and 53.8% of formal and informal sectors, respectively, while men account for 47.1% and 52.9% (KNBS *Economics Survey*, 2023).

This near-equitable distribution underscores a complex interplay of structural barriers and incremental progress in Kenya's evolving labor landscape.

Occupational segregation is a critical driver of Kenya's GPG. Women are overrepresented in care-oriented sectors (e.g., 53.4% in health/social work) and underrepresented in high-productivity industries like mining (12.8%) and manufacturing (22.9%). Vertical segregation compounds this: women dominate lower-tier roles (e.g., domestic work, retail) while men occupy technical and leadership positions. This clustering reflects societal norms that devalue "feminized" roles and restrict women's mobility. For example, 68.3% of working women are in vulnerable employment, compared to 51.8% of men (KNBS *Economic Survey*, 2023). These patterns lead me to hypothesize that non-random occupational sorting—shaped by systemic biases—accounts for significant earnings differentials.

The existing literature has extensively examined the persistent gender pay gap, predominantly attributing disparities to unequal pay for equivalent roles (e.g., Firpo et al., 2018). However, emerging research underscores the critical role of occupational and industrial segregation in shaping aggregate earnings differentials, with gendered clustering in lower-paying sectors amplifying wage inequities (Orraca et al., 2016; Ismail et al., 2017; Goy & Johnes, 2012; Demoussis et al., 2010; Khitarishvili et al., 2018). While both mechanisms—unequal pay and occupational sorting—are acknowledged as key drivers, scholarly emphasis remains disproportionately skewed toward the former. Consequently, significant gaps persist in quantifying the relative contribution of occupational segregation to pay disparities and isolating residual discrimination effects after controlling for observable wage determinants correlated with occupational outcomes. I address these lacunae by conducting a granular decomposition of Kenya's male-female pay differential, explicitly integrating occupational structures into the analytical framework.

Existing research on Kenya's gender wage disparities—including seminal works by Kabubo-Mariara (2003), Agesa et al. (2009, 2013), Omanyo (2021), Abdiaziz and Kiiru (2021), and UN Women (2023)—has predominantly applied the Oaxaca-Blinder decomposition framework (Oaxaca, 1973; Blinder, 1973) and its extensions (Firpo et al., 2009, 2018) to interrogate unequal pay for equivalent roles. However, this methodological paradigm overlooks the structural implications of occupational segregation, as it presupposes the exogenous determination of occupational choices, status, and sectoral hierarchies. Such an assumption becomes untenable if occupational sorting itself reflects labor market discrimination, thereby introducing inherent bias into conventional decomposition models (Liu et al., 2004).

Furthermore, Kenyan scholars such as Kainga (2020), Abdiaziz and Kiiru (2021), and Maina (2021) predominantly emphasize wage discrimination within broad occupational categories. Few Kenyan studies disaggregate earnings functions by occupation or rigorously account for occupational distribution patterns. Instead, methodological approaches they often rely on simplistic occupational dummy variables (Omanyo, 2021; Agessa et al., 2013), which fail to capture the structural dynamics of gendered occupational sorting. By treating occupational distribution as an external variable rather than an endogenous outcome of discriminatory practices, these approaches risk underestimating systemic inequities embedded within Kenya's labor market architecture, thereby overestimating the GPG's "explained" component while obscuring the "unexplained" residual—a critical indicator of systemic discrimination.

To resolve methodological limitations in assessing occupational segregation's role in wage disparities, Brown, Moon, and Zoloth (1980) introduced a seminal framework that endogenizes occupational choice. The BMZ model partitions the gender pay gap into *intra-occupational* disparities (wage differences within the same occupation) and *inter-occupational* disparities (wage differentials arising from gendered occupational sorting). These components are further disaggregated into effects stemming from (1) observable productivity-related characteristics and (2) differential returns to those characteristics, often interpreted as discrimination. Crucially, the inter-occupational component directly quantifies how occupational segregation—driven by systemic barriers or discriminatory practices—contributes to aggregate gender pay gaps (Orraca et al., 2016; Ismail et al., 2017; Goy & Johnes, 2012; Demoussis et al., 2010; Khitarishvili et al., 2018).

The BMZ decomposition framework provides critical insights for designing evidence-based policies to address Kenya's GPG. If *unexplained intra-occupational disparities*—often interpreted as wage discrimination within the same roles—predominate, stringent enforcement of *equal pay for work of equal value* policies becomes imperative to rectify inequitable compensation practices (Ismail et al., 2017). Conversely, if *unexplained inter-occupational disparities* drive the GPG, interventions must target systemic barriers in hiring, promotion, and occupational mobility, such as anti-discrimination legislation and workplace equity audits. Where *explained intra-occupational gaps* arise from disparities in productivity-related characteristics, policy efforts should prioritize closing human capital gaps through gender-responsive upskilling programs, scholarships, and career development initiatives. If *explained inter-occupational gaps* reflect women's underrepresentation in high-wage sectors, strategies must focus on dismantling structural barriers to women's entry into lucrative fields, such as STEM or leadership roles, via mentorship, subsidized training, and sector-specific quotas. Of course, if occupational sorting is largely attributable to observable qualifications, enhancing women's access to advanced education and credentialing could facilitate upward mobility into higher-status occupations.

This study advances Kenya's gender pay gap research through three methodologically distinct contributions. First, it introduces a novel application of the *dissimilarity index* to quantify structural disparities in occupational and sectoral distributions between genders, providing an objective metric for assessing segregation. Second, diverging from prior exogenous treatments of occupational attainment, I model occupational and industrial selection as *endogenous processes*, exploiting observable gender-specific characteristics to simulate a counterfactual occupational distribution for women—assuming parity with male occupational structures. Third, adopting a BMZ decomposition framework, I disentangle *intra-occupational* wage disparities (differences within the same roles) from *inter-occupational* inequities (gaps driven by gendered sectoral sorting). To mitigate biases from occupational misclassification and self-selection—acknowledging that employment decisions reflect multifaceted priorities beyond mere job acquisition—I employ a *reduced-form multinomial logit model* to estimate predicted occupational probability values.

8.2 Literature Review

Demoussis et al. (2010) examined wage differentials between native and immigrant workers in Greece, employing an occupational segmentation framework to disentangle structural drivers of inequality. By estimating occupation-specific wage equations and decomposing disparities into *within-occupation* and *between-occupation* components, the study revealed that 48% of the average wage gap remained unexplained by observable characteristics. Strikingly, 90% of this unexplained residual stemmed from systemic occupational segregation—primarily immigrants' limited access to higher-paying roles—while only 10% arose from intra-occupational inequities. The analysis further highlighted immigrants' overrepresentation in low-wage occupations (e.g., production and unskilled labor) and underrepresentation in lucrative roles such as management, professional services, and legislative positions. Notably, while inter-occupational segregation accounted for the bulk of the unexplained gap, intra-occupational differentials—reflecting unequal pay for similar roles—emerged as a critical, albeit smaller, contributor.

Orraca et al. (2016) analyzed Mexico's gender wage gap using census data and the Brown et al. (1980) decomposition framework and found an increase in wage disparities between men and women from 2000 to 2010. The study identified *intra-occupational inequities*—particularly the unexplained component reflecting differential returns to productivity-related characteristics—as the primary driver of the widening gap. In contrast, *inter-occupational disparities* modestly mitigated wage differentials, underscoring a counterintuitive trend: despite pronounced gendered occupational distribution, segregation did not exacerbate the wage gap. Happily, women faced no systemic barriers to high-paying occupations, even as occupational structures diverged between genders. The persistence of intra-occupational disparities, rooted in unequal returns to human capital, highlights discrimination in wage-setting practices rather than occupational access.

Khitarishvili et al. (2018) investigated the interplay of industrial and occupational segregation in shaping Georgia's gender wage gap, using data taken from the Georgian Household Budget Survey (2004–2015). Applying the Duncan segregation index and Brown-Moon-Zoloth (BMZ) decomposition methods, the study revealed a paradox: while industrial and occupational segregation remained persistently high (as quantified by the Duncan index), wage disparities *within* sectors, industries, and occupations—rather than segregation itself—emerged as the salient drivers of gender earnings inequities. The BMZ decomposition demonstrated that intra-sectoral and intra-occupational wage gaps, especially within the public and private sectors and across skill categories, accounted for the majority of the gender pay gap. Notably, female-dominated industries and occupations—concentrated in sectors resilient to economic shocks like the 2008 crisis—did not exhibit systematically lower wages compared to the economy-wide average. This counterintuitive finding underscores how sectoral growth dynamics, rather than segregation alone, mediate wage outcomes. However, a substantial unexplained residual in both intra- and inter-occupational components points to latent structural barriers, such as discriminatory practices or unobserved productivity constraints, that disproportionately suppress women's earnings.

Ismail et al. (2017) investigated the persistence of gender occupational segregation and wage disparities in Malaysia, utilizing data from the 2011 Malaysian Working Households Survey. While the study acknowledged rising female labor force participation, it underscored enduring inequities in occupational distribution and earnings. Applying Brown et al.'s (1980) wage decomposition framework, the analysis identified *intra-occupational disparities*—specifically unequal returns to comparable roles—as the predominant driver of the gender pay gap. Notably, wage discrimination within occupations emerged as a critical factor, revealing systemic undervaluation of women's labor despite similar occupational classifications.

Goy and Johnes (2012) analyzed Malaysia's gender earnings gap using data from the 2004 Malaysian Population and Family Survey, uncovering counterintuitive findings. Contrary to conventional assumptions, occupational segregation was found to *mitigate* earnings disparities between men and women. Applying decomposition methods, the study attributed the majority of the gap to the *unexplained intra-occupational residual*—interpreted as discrimination within roles—rather than occupational sorting itself. This residual, reflecting systemic wage-setting biases, dominated the within-occupation component, while differences in observable characteristics played a diminished role. The authors posited that hierarchical segregation—women's concentration in lower-tier positions within the same occupation—and sample selection effects partially explained the intra-occupational inequities. Paradoxically, occupational segregation's net effect reduced the aggregate earnings gap, as female-dominated roles in Malaysia did not exhibit the wage penalties typically associated with gendered sectoral clustering.

Herrera et al. (2019) analyzed Nicaragua's gender wage disparities using data from the 2009 Living Standards Measurement Survey and found that occupational segregation significantly exacerbated income inequities. Women were disproportionately concentrated in lower-paying, female-dominated occupations, with wage gaps intensifying in highly segregated sectors. This systematic undervaluation of roles predominantly held by women underscored how occupational sorting entrenches gender-based economic marginalization in Nicaragua's labor market. In contrast, Chakraborty (2020) examined India's gender pay differentials across public and private sectors using the 2018–2019 Periodic Labor Force Survey. Employing the Oaxaca-Blinder decomposition and Brown-Moon-Zoloth (BMZ) technique for robustness, the study identified occupational discrimination as a critical driver of wage gaps, particularly in rural areas where disparities were more pronounced. Counterfactual analysis suggested eliminating occupational segregation could reduce average wage gaps by 57% in rural India and 67% in urban India.

Maina (2021) investigated the nexus between occupational segregation and gender wage gaps in Kenya using data from the 2019 Quarterly Labor Force Survey. The study revealed a pronounced wage disparity, with male workers earning 58.8% more than female counterparts on average. Applying the Duncan segregation index, the analysis quantified occupational segregation, indicating that 42.73% of women would need to transition to male-dominated roles to achieve full labor market integration. The OLS estimates further demonstrated an inverse relationship between female wage levels and the proportion of women within occupations, aligning with the *crowding model theory*—which posits that wage suppression arises from the concentration of women in oversaturated, low-paying sectors. However, inter-occupational segregation accounted for a negligible 1.89% of the wage gap, suggesting that systemic wage discrimination *within* occupations, rather than sectoral sorting alone, underpins Kenya's persistent inequities.

Complementing this, Kianga (2020) explored structural determinants of women's occupational choices using the 2014 Kenya Demographic and Health Survey. A multinomial logit model categorized occupations into professional, agricultural, household, service, and manual labor, identifying key socioeconomic drivers: higher education and urban residency correlated with entry into professional roles, while marital status, parity (childbearing), and larger household size increased the likelihood of informal or unpaid work (e.g., household and agricultural labor). Wealth disparities and rural-urban divides further entrenched occupational stratification, highlighting how intersecting socioeconomic factors constrain women's labor market mobility

8.3 Methodology: The BMZ Decomposition

The Brown-Moon-Zoloth (BMZ) decomposition framework (Brown et al., 1980) offers a robust methodology to disentangle the gender pay gap into two distinct components: *intra-occupational disparities* (wage differences within the same occupation) and *inter-occupational disparities* (wage gaps stemming from unequal gender representation across occupations). The intra-occupational component captures inequities in pay for comparable roles, often attributed to discrimination or differential returns to human capital. In contrast, the inter-occupational component quantifies how occupational segregation—the systemic clustering of women in lower-paying sectors and men in higher-paying ones—contributes to aggregate wage differentials.

Building on the foundational work of Mincer (1974), which models earnings as a function of individual and job-related characteristics, I operationalize the BMZ decomposition to analyze Kenya's gender pay gap. The Mincerian earnings equation forms the methodological backbone, expressed for an individual *i* in occupation *j* as:

$$lnW_{ij} = \alpha_j + \sum_{j=1}^{k} \beta_j X_{ij} + \varepsilon_{ij} \qquad j = 1,2,3 \dots \dots J, \tag{8.1}$$

where lnW_{ij} denotes the natural logarithm of the earnings for individual i in occupation $j = 1,2,3 \dots \dots J$. X_{ij} represents the vector of observable individual's characteristics, α_j and β_j are vectors of occupation-specific intercepts and coefficients, ε_{ij} is the random stochastic term which has zero expected value, and *J* signifies the total occupational categories considered.

To isolate gender-specific earnings determinants, separate Mincer regressions are estimated for male (*m*) and female (*f*) workers. That is,

$$lnW_{ij}^{m} = \alpha_j + X_{ij}^{m}\hat{\beta}_j + \varepsilon_{ij}^{m} \tag{8.2}$$

$$lnW_{ij}^{f} = \alpha_j + X_{ij}^{f}\hat{\beta}_j + \varepsilon_{ij}^{f} \tag{8.3}$$

Let $ln\overline{W}^{m}$and $ln\overline{W}^{f}$ denote the mean natural logarithm of earnings for male and female workers, respectively, while P_j^m and P_j^f represent the observed proportions of men and women employed in occupation j. To isolate the structural drivers of earnings disparities, we contrast these observed distributions with a *counterfactual occupational distribution* for women ($\hat{P}_f$), which simulates female occupational attainment under parity with male occupational structure. Following Brown et al. (1980), the aggregate logarithmic pay differential, $(\overline{lnW^{m}} - \overline{lnW^{f}})$, is decomposed as

$$\overline{lnW^{m}} - \overline{lnW^{f}} = \sum_{j=1}^{J} (P_j^m \overline{lnW^{m}} - P_j^f \overline{lnW^{f}}) \qquad j = 1,2, \dots \dots J \tag{8.4}$$

Under the Mincer framework (Mincer, 1974), the gender-specific earnings equations for males (m) and females (f) are estimated separately. Assuming the error term is zero at the mean values of explanatory variables, the average logarithmic wages for each gender can be expressed as

$$\overline{lnW}^m - \overline{lnW}^f = \sum_{j=1}^{J} P_j^f \left(\hat{\beta}_j^m \bar{X}_j^m - \hat{\beta}_j^f \bar{X}_j^f\right) + \sum_{j=1}^{J} \hat{\beta}_j^m \bar{X}_j^m \left(P_j^m - P_j^f\right) \quad (8.5).$$

In consistent with Brown et al. (1980), the first term on the right-hand side of Equation (8.5) captures *intra-occupational* wage differentials attributable to disparities in observable productivity-related characteristics across genders within the same occupation. Termed the within-explained (WE) component, this reflects justifiable earnings differences linked to measurable human capital endowments. The second term represents *inter-occupational* wage gaps arising from unequal participation rates of men and women across occupations, labeled the between-explained (BE) component. Mirroring the Oaxaca-Blinder (1973) decomposition logic, Brown et al. (1980) further dissected both the WE and BE components into

$$\sum_{j=1}^{J} P_j^f (\hat{\beta}_j^m \bar{X}_j^m - \hat{\beta}_j^f \bar{X}_j^f) = \sum_{j=1}^{J} P_j^f \hat{\beta}_j^m (\bar{X}_j^m - \bar{X}_j^f) + \sum_{j=1}^{J} P_j^f \bar{X}_j^f \left(\hat{\beta}_j^m - \hat{\beta}_j^f\right) \quad (8.6).$$

$$\sum_{j=1}^{J} \hat{\beta}_j^m \bar{X}_j^m \left(P_j^m - P_j^f\right) = \sum_{j=1}^{J} \hat{\beta}_j^m \bar{X}_j^m (P_j^m - \hat{P}_j^f) + \sum_{j=1}^{J} \hat{\beta}_j^m \bar{X}_j^m \left(\hat{P}_j^f - P_j^f\right), \quad (8.7).$$

where $\hat{P}_j^f$ represents the hypothetical occupational distribution structure for women, assuming they have the same occupational distribution as men. The second term in Equation (8.6) reflects *intra-occupational unexplained* (WU) disparities, capturing wage differentials arising from vertical or hierarchical segregation—unequal representation of genders in higher-paying roles within the same occupation due to unobserved factors (e.g., implicit bias, promotion barriers) or unequal returns to equivalent qualifications (Salardi, 2013). Equation (8.7) quantifies *between-unexplained* (BU) disparities, signifying wage gaps attributable to horizontal occupational segregation, where systemic barriers or divergent occupational preferences limit women's access to specific sectors (Liu et al., 2004). Hence, combining equations (8.6) and (8.7), Equation (8.5) can be rewritten as follows:

$$\overline{lnW}^m - \overline{lnW}^f = \sum_{j=1}^{J} P_j^f \hat{\beta}_j^m (\bar{X}_j^m - \bar{X}_j^f) + \sum_{j=1}^{J} P_j^f \bar{X}_j^f \left(\hat{\beta}_j^m - \hat{\beta}_j^f\right) + \sum_{j=1}^{J} \hat{\beta}_j^m \bar{X}_j^m (P_j^m - \hat{P}_j^f) + \sum_{j=1}^{J} \hat{\beta}_j^m \bar{X}_j^m \left(\hat{P}_j^f - P_j^f\right), \qquad (8.8).$$

where P_j^m and P_j^f represent the proportion of male and female workers employed in occupation category j, respectively. The term $\hat{P}_j^f$ refers to the hypothetical proportion of women in the sample who would be in the same occupation j if they had the same occupational structure as men. The *counterfactual occupational distribution* for female workers is derived by applying male occupational attainment patterns—assumed to reflect nondiscriminatory norms—to female workers' observable productivity-related characteristics. This simulated distribution isolates disparities attributable solely to gendered differences in human capital endowments rather than systemic bias. Consequently, the divergence between the *actual* male occupational distribution P_j^m and the *predicted* female distribution $\hat{P}_j^f$ captures nondiscriminatory gaps rooted in productivity factors (Sung et al., 2001).

The decomposition shown in Equation (8.8) can be expressed as the sum of four terms, comprising explained and unexplained components. The first term on the right-hand side represents the intra-occupational explained (WE): Wage differences *within* occupations justified by observable productivity characteristics. The second term is the intra-occupational unexplained (WU): Residual wage gaps *within* occupations attributable to discrimination, unobserved biases, or unequal returns to equivalent qualifications. The third term represents the inter-occupational explained (BE): Wage differences *across* occupations driven by gendered human capital disparities influencing occupational sorting. And the fourth term represents the inter-occupational unexplained (BU): Wage gaps *across* occupations stemming from systemic barriers (e.g., hiring discrimination, cultural norms) that restrict women's access to high-wage sectors.

A methodological cornerstone of the BMZ decomposition is the construction of a *counterfactual occupational distribution* for women, free from systemic discrimination. This requires modeling occupational attainment to simulate how women would be distributed across occupations if their sorting mirrored nondiscriminatory norms. Brown et al. (1980) addressed this by employing a *reduced-form multinomial logit model*, which estimates the probability of an individual i being employed in occupation j based on observable characteristics, while endogenously modeling occupational choice. The MNL framework accounts for self-selection and labor market constraints, generating predicted probabilities that reflect how systematic predictors—rather than discriminatory practices—shape occupational outcomes. These probability values can be defined as follows:

$$P_{ij} = Prob\left(Y_i = OCC_j\right) = \frac{\exp(Z_i\hat{\gamma}_j)}{1 + \sum_{j=1}^{J}\exp(Z_i\hat{\gamma}_j)} + \varepsilon_{ij} \quad i = 1,2 \ldots.N \quad j = 1,2 \ldots..J, \qquad (8.9).$$

where Z_i denotes a vector of external labor market factors assumed to influence occupational choice. $\hat{\gamma}_j$ is a vector of coefficients corresponding to occupation j, and ε_{ij} is the random stochastic term.

To construct the counterfactual occupational distribution, the parameters estimated from the male occupational attainment model (Equation 8.9) are applied to female workers' observable characteristics. This simulates the occupational distribution women would exhibit under male-normed, nondiscriminatory sorting. For each female worker, predicted probabilities of belonging to occupation j are generated via the multinomial logit model, then aggregated across the sample to derive $\hat{P}_j^f$.

The process for estimating this wage decomposition comprises three main steps. First, a probability model, specifically a multinomial logit model, determines the predicted occupational distribution for females ($\hat{P}_j^f$). Second, wage functions are estimated for each occupation and gender category to obtain the estimated coefficients $\hat{\beta}_j^m$ and $\hat{\beta}_j^f$. Lastly, the information gathered from the first two steps is used to calculate the components of the gender paya gap.

The disparities between the estimated occupational distribution of women, $\hat{P}_j^f$, and their actual values, P_j^f, may stem from selection bias in how women are assigned to different occupations. This study addresses this issue by employing a methodology that considers sample selection bias when estimating wage regressions for both men and women. First, separate multinomial logit models are estimated for the samples of men and women. The inverse Mill's ratio ($\hat{\lambda}_{ij}$) is then calculated using the information obtained from the multinomial logit estimations.

In the final step, the calculated Mill's ratios are included as independent variables in the estimation of the wage regressions, as follows:

$$lnW_{ij}^{m} = X_{ij}^{m}\beta_{j}^{m} + \hat{\lambda}_{ij}^{m}\theta_{j}^{m} + \mu_{ij}^{m} \quad j = 1,2,3 \ldots.., \tag{8.10}$$

$$lnW_{ij}^{f} = X_{ij}^{f}\beta_{j}^{f} + \hat{\lambda}_{ij}^{f}\theta_{j}^{f} + \mu_{ij}^{f} \quad j = 1,2,3 \ldots.., \tag{8.11}$$

where $\hat{\lambda}_{ij}$ represents the calculated inverse Mill's ratios, and θ_j denotes the parameters to be estimated. By incorporating these variables, the potential bias resulting from the nonrandom distribution of occupational choice is accounted for in the decomposition analysis. By modifying Equation (8.8) accordingly, the gender wage gap is broken down into components, including explained and unexplained portions, inter-and intra-occupational wage differentials, and the term addressing sample selectivity bias. Including the selectivity bias correction terms (Lee 1983; Heckman, 1979), the sum of mean logarithmic earnings differentials across all occupational categories in Equation (8.8) can be expressed as follows:

$$\begin{aligned}\overline{lnW}^{m} - \overline{lnW}^{f} = &\sum_{j=1}^{J} P_j^f \hat{\beta}_j^m (\bar{X}_j^m - \bar{X}_j^f) + \sum_{j=1}^{J} P_j^f \bar{X}_j^f \left(\hat{\beta}_j^m - \hat{\beta}_j^f\right) + \sum_{j=1}^{J} \hat{\beta}_j^m \bar{X}_j^m (P_j^m - \hat{P}_j^f) \\ &+ \sum_{j=1}^{J} \hat{\beta}_j^m \bar{X}_j^m \left(\hat{P}_j^f - P_j^f\right) + \sum_{j=1} (P_j^m \hat{\lambda}_j^m \theta_j^m - P_j^f \hat{\lambda}_j^f \theta_j^f),\end{aligned} \tag{8.12}$$

8.4 Results and Discussion

8.4.1 Log Monthly earnings by gender and occupation

The analysis of mean log monthly earnings across occupational categories reveals notable disparities in income distribution and gender-based pay differentials. As shown in Table 25, the occupation "Legislators, administrators, and managers" represents the highest-earning group with 10.333 log points, while "Skilled agriculture, forestry, and fishery workers" rank lowest at 7.898 log points. The overall mean monthly earnings across all occupations average 8.818 log points, with women experiencing an earnings disadvantage of 0.114 log points relative to men (full sample). However, gender disparities vary significantly by occupational sector. Women exhibit higher earnings than men in six categories: "Legislators, administrators, and managers"; "Clerical jobs"; "Technicians and associate professionals"; "Plant and machine operators and assemblers"; "Craft and trade-related works"; and "Elementary occupations." Conversely, men earn more in

"Professional," "Service and market sales workers," and "Skilled agriculture, forestry, and fishery works," with the largest gap (0.359 log points) observed in the latter category.

Strikingly, the occupational hierarchy displays an inverse relationship between wage differentials and occupational status. At the upper end of the distribution, women hold a wage advantage (−0.161 log points), whereas men dominate at the lower end, particularly in the agricultural sector. Notably, despite the male-dominated composition of "Plant and machine operators and assemblers" and "Craft and trade-related works," women in these sectors demonstrate higher mean earnings—potentially attributable to the limited sample size of female workers in these fields, which may skew comparative earnings data.

The data presented in Table 25 highlight a pronounced gender wage disparity across occupational tiers, with women facing earnings disadvantages of 0.283 log points in "Professionals," 0.387 log points in "Service workers, shop, and market sales workers," and 0.359 log points in "Skilled agriculture, forestry, and fishery works." These figures indicate that there is a distinct gradient in the unadjusted gender pay gap across the occupational hierarchy. Notably, the disparity is smallest in high-paying occupations at the upper echelons of the distribution, escalates moderately in middle-income roles, and peaks in the lowest-paying sectors. This pattern suggests that the female wage disadvantage diminishes at the top of the occupational spectrum but gradually increases toward lower-income occupations, with the most significant gap observed in sectors such as agriculture and forestry.

Table 25: Log monthly earnings by occupation and gender

Occupation Group	Men	Women	Raw pay gap	Full sample
Occ1: Legislators, Administrators, and Managers	10.276 (1.414)	10.437 (0.775)	-0.161	10.333 (1.225)
Occ2: Professionals	10.245 (1.056)	9.962 (1.121)	0.283	10.095 (1.099)
Occ4: Secretarial, Clerical services, and related workers	9.913 (1.239)	10.041 (1.015)	-0.128	10.0029 (1.082)
Occ3: Technicians and Associate professionals	9.782 (1.255)	10.021 (1.410)	-0.239	9.844 (1.298)
Occ5: Service workers, shop, and market sales workers	9.166 (1.264)	8.779 (1.380)	0.387	9.00487 (1.327)
Occ8: Plant and Machine operators and assemblers	8.846 (1.518)	9.259 (0.813)	-0.413	8.874 (1.484)
Occ7: Craft and related trade workers	8.714 (1.320)	8.989 (1.058)	-0.275	8.740 (1.3003)
Occ9: Elementary Occupations	8.340 (1.184)	8.342 (1.075)	-0.002	8.341 (1.131)
Occ6: Skilled Agriculture, Forestry, and Fishery workers	8.053 (1.493)	7.694 (1.489)	0.359	7.898 (1.501)
All Occupations	8.860 (1.502)	8.746 (1.546)	0.114	8.818 (1.519)
Observations	4,210	2,443		6,653

Source: Author's calculations (2024) based on KCHS-2021 data. Standard errors are in parentheses. Note: Individuals aged between 15 and 65 years. Monthly earnings are in natural logarithms in Kenya Shilling (Ksh.)

8.4.2 The Occupational and Industrial Structure in Kenya

The occupational distribution of women's employment in Kenya exhibits notable patterns across industries and hierarchical tiers, as detailed in Table 26. At the extremes of the occupational hierarchy, women are disproportionately represented in both the highest-paying category ("legislators, administrators, and managers") and the lowest-paying sector ("skilled agriculture, forestry, and fishery"). This polarization contrasts with trends in middle-tier occupations, where men dominate production-related roles such as "plant and machine operators and assemblers," "craft and trade workers," and "technicians and associate professionals." Notably, women maintain higher participation rates than men in the three highest-paying occupational groups, while also constituting a significantly larger share of workers in "elementary occupations"—a category characterized by low wages and minimal skill requirements.

Table 26: Occupational distribution by primary occupation (KeSCO-2022) classification in Kenya

Occupation Group	Male employees (%)	Female employees (%)	Full sample (%)
Occ1: Legislators, Administrators, and Managers	1.26	1.78	1.45
Occ2: Professionals	10.35	19.79	13.74
Occ4: Secretarial, Clerical services, and related workers	0.5	1.98	1.06
Occ3: Technicians and Associate professionals	4.16	3.28	3.84
Occ5: Service workers, shop, and market sales workers	16.25	21.22	18.04
Occ8: Plant and Machine operators and assemblers	14.55	2.67	10.28
Occ7: Craft and related trade workers	23.90	3.88	16.70
Occ9: Elementary Occupations	11.67	21.58	15.24
Occ6: Skilled Agriculture, Forestry, and Fishery workers	17.31	23.86	19.65
All Occupations	100	100	100

Source: Author's calculations (2024) based on KCHS-2021 data. Note: Individuals Aged 15 and above. Weighted data

Table 27 further elucidates gendered industrial participation patterns, revealing distinct concentrations across sectors. Women have a higher representation in the primary sector, specifically skilled agriculture, as well as in several tertiary industries: Tertiary Sector 6 (domestic workers in private households), Tertiary Sector 5 (education, health, social work, and community services), and Tertiary Sector 2 (wholesale/retail trade, hospitality, and food services). Conversely, men dominate employment in manufacturing, mining, and extractive industries. Within the broader service sector, male participation is notably higher in Tertiary Sector 1 (utilities, construction), Tertiary Sector 3 (transport, logistics, communications, and finance), and Tertiary Sector 4 (real estate, business services, public administration, and social security)[24]. These disparities underscore a gendered bifurcation in Kenya's labor market, where women are disproportionately concentrated in care-oriented, agricultural, and informal service roles, while men prevail in technical, industrial, and high-value service sectors.

Table 27: Industrial segregation by gender

Industry of work	**Male employees (%)**	**Female employees (%)**	**Full sample (%)**
Primary sector	23.91	29.84	26.05
Manufacturing	7.46	3.69	6.11
Mining and Extractives	2.32	0.25	1.58
Service sector			
Tertiary sector 1	19.82	1.51	13.23
Tertiary sector 2	7.96	12.16	9.47
Tertiary sector 3	15.26	2.64	10.72
Tertiary sector 4	8.92	6.24	7.96
Tertiary sector 5	12.19	31.96	19.30
Tertiary sector 6	2.15	11.71	5.59

Source: Author's calculations (2024) based on KCHS-2021 data. Note: Individuals Aged 15 and above. Weighted data.

To analyze gender-based segregation across occupational sectors, I employ the Duncan and Duncan (1955) dissimilarity index, a methodological tool widely utilized in scholarly research to quantify the proportion of individuals who would need to shift sectors to achieve parity in occupational or industrial distribution. This approach was applied extensively in prior studies, including works by Hori (2009), Khitarishvili et al. (2018), Orraca et al. (2016), and Maina (2021), to assess patterns of sectoral segregation. The index is mathematically represented as follows:

$$D = \frac{1}{2}\sum_{i=1}^{N}\left| {}^{M_i}/_{M} - {}^{W_i}/_{W} \right|, \qquad (8.13).$$

where D is interpreted as measuring the proportion of men (women) workers required to change occupations and industries of work to obtain the same occupational and industrial distribution generated by women (men) workers. M_i and W_i denote the number of male and female workers in occupation i, respectively, and M and W represent the total male and female workforce across all occupations. The index ranges from 0 (complete integration) to 1 (total segregation),

[24] The service industry is disaggregated into six sectors: tertiary sector 1 (electricity, gas and water supply, construction), tertiary sector 2 (wholesale and retail trade, hotels and restaurants), tertiary sector 3 (transport, storage and communications, financial intermediation), tertiary sector 4 (real estate, renting and business activities, public administration, compulsory social security), tertiary sector 5 (education, health and social work, other community social and personal service activities) and tertiary sector 6 (private households with employed persons).

with higher values reflecting greater gender disparities in sectoral representation. Here, I quantify gender segregation across three dimensions of Kenya's labor market: employment sector[25]: formal sector (public and private), and informal sector, nine industrial classifications, and nine occupational categories aligned with the KeSCO-2022 framework. The indices are computed to assess the extent to which men and women are unevenly distributed within these groupings, reflecting structural disparities in labor market participation.

Table 28: Dissimilarity Index for KeSCO-2022 occupations, industrial classification, and employment sectors

Occupation Category	Dissimilarity index	Industry category	Dissimilarity index	Sector of employment	Dissimilarity index
Occ1: Legislators, Administrators, and Managers	0.005189	primary sector	0.059335	Public sector	0.07998
Occ2: Professionals	0.094391	manufacturing	0.037715	private formal	0.008541
Occ3: Technicians and Associate professionals	0.014346	tertiary sector 1	0.183123	Private informal	0.088521
Occ4: Secretarial, Clerical services, and related workers	0.049657	tertiary sector 2	0.042		
Occ5: Service workers, shop, and market sales workers	0.065121	tertiary sector 5	0.197696		
Occ6: Skilled Agriculture, Forestry, and Fishery workers	0.099022	tertiary sector 3	0.126169		
Occ7: Craft and related trade workers	0.008758	tertiary sector 4	0.02683		
Occ8: Plant and Machine operators and assemblers	0.200148	mining/extractives	0.020753		
Occ9: Elementary Occupations	0.11882	tertiary sector 6	0.095561		
Dissimilarity Index $\frac{1}{2}\sum_{i=1}^{N}\left|{}^{M_i}/_{M} - {}^{W_i}/_{W}\right|$	**0.369**		**0.30**		**0.0885**

Source: Author's calculations (2024) based on KCHS-2021 data. Weighted data

The Duncan dissimilarity index, as presented in Table 28, quantifies gender segregation across Kenya's labor market, revealing that 8.9 percent of women (men) would need to reallocate across employment sectors (public sector, private formal sector, or informal sector) to achieve parity with men's distribution. Occupational and industrial disparities are more pronounced, requiring 37 percent and 30 percent of women (men), respectively, to shift occupations or industries to mirror men's distribution patterns. These findings suggest significant gender-driven labor market segmentation, with women disproportionately concentrated in sectors such as agriculture and elementary occupations. To attain equilibrium, female (male) workforce redistribution would primarily involve increased entry into higher-status roles—including "legislators, administrators, and managers"; "professionals"; "technicians and associate professionals"; "service and trade-related roles"; and "clerical positions"—while reducing representation in lower-paying agricultural and elementary occupations. Notably, Kenya's occupational dissimilarity index has declined over time, with Maina (2021) reporting a value of

[25] Private sector (formal) workers are defined as individuals employed in private businesses, excluding "Jua-Kali" and faith-based organizations (FBOs). The informal sector comprises individuals employed in informal private enterprises, commonly referred to as "Jua-Kali" in the Kenyan labor market, and those working in non-governmental organizations (NGOs) and domestic employees in private households.

0.4273 in 2019, based on Quarterly Labor Force Survey data. This trend contrasts with international benchmarks: research in Georgia, for instance, documents dissimilarity indices of 0.1774 (employment sector), 0.4757 (industry), and 0.3729 (occupation), reflecting comparatively lower sectoral segregation but higher industrial and occupational imbalances (Khitarishvili et al., 2018).

8.4.3 Occupation-Specific Earnings Estimation Analysis

Tables 29 and 30 present occupation-specific wage estimates, adjusted for sample selection bias. To address systematic differences in job characteristics between men and women (Goy & Johnes, 2012), I correct for sample selectivity-bias in the occupation-specific earnings equation using the Heckman two-step model. This involves estimating individuals' occupational choices within a multinomial logit framework in the first stage and incorporating the inverse Mills ratio as an additional explanatory variable in the wage estimations.

The estimated coefficients vary significantly across occupational groups, reflecting differences in how covariates relate to earnings among occupations. Potential work experience displays both linear and nonlinear associations with earnings for men and women, though it is statistically more significant for male employees across all occupational categories. This disparity may stem from career interruptions among female employees due to childcare responsibilities, limiting their accumulation of seniority effects (Teo, 2003). Additionally, the results for both men and women exhibit expected signs for age and age-squared across occupations, supporting the inverted U-shaped relationship between age and earnings.

The findings highlight the critical role of education in human capital development as higher education levels lead to significantly greater wage returns. Using primary education as the reference category, male workers with a bachelor’s degree earn substantially more across various occupations: managerial/administrative roles, professional roles, associate professional/technician roles, and service roles. Similarly, female workers with a bachelor’s degree experience even larger wage premiums: managerial/administrative roles, professional roles, associate professional/technician roles, clerical roles, service roles, and skilled agriculture roles, compared to those with only primary education, all else being equal. A comparable pattern is observed for both male and female workers with postgraduate education. Notably, the returns on education vary considerably across occupations, with highly skilled roles, such as professional and associate professional/technician positions, yielding higher returns compared to low-skilled occupations like elementary roles.

Table 29: The Mincer OLS earnings equation for male employees

VARIABLES	Occ1	Occ2	Occ3	Occ4	Occ5	Occ6	Occ7	Occ8	Occ9
Potential experience	0.0342	0.0828***	0.0732	0.253	-0.0409	0.0558*	0.0527*	0.121***	0.0449*
	(0.1482)	(0.0293)	(0.0557)	(0.578)	(0.0299)	(0.0252)	(0.0284)	(0.0406)	(0.0248)
experience2	-0.000239	-0.000932***	-0.000882	-0.00267	0.000481	-0.000592*	-0.000508	-0.00128*	-0.00065*
	(0.0017)	(0.000353)	(0.000694)	(0.0066)	(0.000368)	(0.000318)	(0.000360)	(0.000512)	(0.000314)
Married	-0.800	0.222*	-0.0417	-3.066	0.227*	-0.0985	0.0148	-0.147	0.0480
	(0.661)	(0.131)	(0.211)	(2.478)	(0.131)	(0.134)	(0.127)	(0.181)	(0.136)
Secondary	0.442	0.424***	0.132	0.5204	0.223**	0.31009**	0.1000	0.384***	0.216*
	(0.639)	(0.162)	(0.229)	(1.350)	(0.107)	(0.1066)	(0.0969)	(0.131)	(0.114)
Diploma	1.425	0.967***	0.944***	6.624	0.744***	0.3645	0.612**	1.117***	0.447
	(0.874)	(0.208)	(0.338)	(4.779)	(0.191)	(0.285)	(0.217)	(0.293)	(0.317)
Bachelors	1.131*	1.417***	1.0479***	2.257	1.288***	0.930	0.8143*	0.874**	0.491
	(0.667)	(0.178)	(0.313)	(3.508)	(0.221)	(0.638)	(0.317)	(0.441)	(0.585)
Post-graduate	1.758	2.0450***	2.672***	9.607	1.570***	Dropped[a]	1.755	0.246	Dropped[a]
	(1.285)	(0.237)	(0.718)	(9.349)	(0.5002)		(1.281)	(1.672)	
Post-primary	-0.243	0.523	-0.938	Dropped[a]	-0.0930	0.458	-0.1305	0.153	0.0999
	(1.924)	(0.339)	(0.711)		(0.374)	(0.355)	(0.227)	(0.407)	(0.360)
Tenure	-0.00348	0.0241***	0.0350**	-0.00266	0.0241**	-0.0107*	-0.00321	0.0000736	-0.000691
	(0.0292)	(0.00579)	(0.0117)	(0.0507)	(0.00828)	(0.00620)	(0.00646)	(0.0113)	(0.00776)
Hours	0.0126	-0.00635**	-0.00376	0.1094	-0.00231	0.0234***	0.0122***	0.0004071	0.0125***
	(0.0139)	(0.00276)	(0.00503)	(0.144)	(0.00244)	(0.00292)	(0.00306)	(0.00313)	(0.00295)
Firm size	0.0336	0.0534*	0.0221	0.0908	0.1037***	0.0982**	0.1229***	0.184***	0.1103***
	(0.0822)	(0.0282)	(0.044)	(0.217)	(0.0276)	(0.0296)	(0.0350)	(0.0341)	(0.0304)
Public sector	1.275	-0.0364	0.883***	-4.181	0.561***	1.0123*	0.6402*	0.486	0.0403
	(0.798)	(0.144)	(0.213)	(4.173)	(0.162)	(0.454)	(0.353)	(0.306)	(0.312)
Private formal	0.455	-0.0921	0.844***	-3.194	0.333**	0.911***	0.439**	0.126	0.1663
	(1.263)	(0.157)	(0.220)	(4.360)	(0.124)	(0.275)	(0.191)	(0.201)	(0.282)
Urban	-0.3001	0.1352*	0.147	1.594	0.253**	0.223	0.172*	0.0557	0.287*
	(0.387)	(0.0792)	(0.158)	(1.0703)	(0.0963)	(0.137)	(0.0927)	(0.126)	(0.121)
Christian	-0.355	-0.122	-0.107	2.971	-0.0766	0.519*	0.223	0.159	0.0380
	(0.992)	(0.196)	(0.377)	(5.451)	(0.251)	(0.141)	(0.166)	(0.233)	(0.187)
Islamic	0.0673	-0.0108	0.134	3.837	0.148	0.882***	0.399*	0.785***	0.0995
	(1.118)	(0.230)	(0.431)	(4.814)	(0.282)	(0.358)	(0.211)	(0.287)	(0.312)
Union member	-0.5884	0.378***	0.323	-1.247	0.121	-0.209	0.193	0.201	0.312
	(0.383)	(0.084)	(0.230)	(1.356)	(0.2002)	(0.268)	(0.394)	(0.251)	(0.472)
Manufacturing	Dropped[a]	-0.556	0.0592	Dropped[a]	0.149	0.5617	0.0211	0.451	-0.0162
		(0.438)	(0.613)		(0.371)	(0.366)	(0.408)	(0.429)	(0.357)
Tertiary sector 1	Dropped[a]	0.315	-0.509	Dropped[a]	0.910	0.948	0.088	0.817	-0.2667*
		(0.341)	(0.309)		(0.778)	(0.986)	(0.388)	(0.524)	(0.157)
Tertiary sector 2	Dropped[a]	-0.238	0.197	7.264	0.309	0.733	0.2066	0.392	0.189
		(0.403)	(0.610)	(9.375)	0.241)	(0.787)	(0.485)	(0.794)	(0.231)
Tertiary sector 5	-1.551	-0.459**	-0.325	5.758	0.538**	0.663	-0.1799	0.4508	0.298
	(1.718)	(0.222)	(0.315)	(8.968)	(0.262)	(0.728)	(0.528)	(0.579)	(0.232)
Tertiary sector 3	-0.0636	-0.0657	0.0128	3.895	0.439	Dropped[a]	-0.0804	0.332	0.0314
	(1.887)	(0.263)	(0.317)	(4.174)	(0.276)		(0.421)	(0.402)	(0.251)
Tertiary sector 4	0.0739	-0.00584	-0.156	8.941	0.498**	0.426	-0.352 0	0.859	0.366
	(1.651)	(0.274)	(0.316)	(9.556)	(0.246)	(1.062)	(0.759)	(1.035)	(0.236)
Tertiary sector 6	Dropped[a]	Dropped[a]	0.893	Dropped[a]	0.5903	1.121*	0.157	1.749*	0.192
			(0.966)		(0.382)	(0.557)	(0.742)	(1.047)	(0.175)
Mining/extractives	Dropped[a]	-1.306*	Dropped[a]	Dropped[a]	0.485	0.116	0.156	0.332	-0.0978
		(0.784)			(0.657)	(1.364)	(0.4900)	(0.415)	(0.297)
Inverse mills ratio	1.436	0.278	0.711	14.573	0.171	-0.0352	0.349	0.625	-0.252
	(1.809)	(0.405)	(0.624)	(10.965)	(0.350)	(0.273)	(0.311)	(0.443)	(0.286)
Constant	6.552	7.182***	6.613***	-24.476	8.164***	5.072***	5.558***	4.110***	6.738***
	(4.063)	(0.776)	(1.422)	(21.871)	(0.766)	(0.560)	(0.777)	(1.018)	(0.586)
Observations	84	454	179	27	608	879	889	550	540
R-squared	0.2780	0.5309	0.5436	0.8008	0.3462	0.2105	0.1195	0.2447	0.1668

	Prob > F= 0.3377	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.5820	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000

Source: Author's calculations (2024) based on KCHS-2021 data. Note: Individuals aged between 15 and 65 years. Standard deviation in brackets, *** p<0.01, ** p<0.05, * p<0.1. Dropped[a] -There were no male respondents with this characteristic in this specific occupation category.

Women are more likely than men to shoulder household responsibilities due to traditional gender roles within families (Goy & Johnes, 2011), which is expected to result in an earnings penalty for married women. The findings reveal a wage penalty for married women in four occupational categories: professionals, associate professionals/technicians, secretarial/clerical roles, and skilled agriculture. However, this penalty is statistically significant only for female workers in skilled agriculture. While not statistically significant across all occupations, women in highly skilled roles generally face a higher wage penalty for being married compared to those in low-skilled occupations.

Men experience an earnings premium linked to marriage, although this effect is statistically insignificant across all occupational categories except for professionals and service workers. This aligns with the literature suggesting that marriage is often perceived as a marker of stability, discipline, and motivation, which can influence employers' perceptions and wage decisions. The advantages associated with this status indicate that it serves as a productivity or motivational signal to employers (Ntuli, 2007). These findings are consistent with Goy and Johnes (2012), but contrast with those of Ismail et al. (2017).

Employment in the public sector has a positive and significant association with wages for both men and women in skilled occupations. Specifically, men working as associate professionals/technicians, service workers, skilled agriculture/forestry/fishery workers, and craft and related trade workers earn higher wage premiums in the public sector compared to their private sector counterparts. Similarly, women in professional and service roles receive higher wage premiums in the public sector than in the private sector. However, women in clerical and secretarial positions earn higher wage premiums in the private sector compared to the public sector.

Furthermore, women in skilled agriculture, forestry, and fishery roles, as well as craft and trade-related occupations, earn significantly higher wages in the private sector compared to the public sector. Across genders, women in the public sector's service industry receive a higher wage premium than their male counterparts. In the private sector, women in craft and trade-related roles and the service sector earn higher wages than men, while men in skilled agriculture, forestry, and fishery occupations outearn women. Among women in the private sector, craft and trade-related occupations yield higher returns than other categories, whereas for men, skilled agriculture, forestry, and fishery roles are more lucrative. Overall, the public sector's wage premium is more pronounced for men (significant in four occupation categories) than for women.

Table 30: The Mincer OLS earnings equation results for female employees

VARIABLES	Occ1	Occ2	Occ3	Occ4	Occ5	Occ6	Occ7	Occ8	Occ9
Potential experience	0.0452	0.154***	0.102	0.141*	0.00766	0.0781**	0.275**	0.0288	0.0180
	(0.0779)	(0.0307)	(0.129)	(0.0822)	(0.0428)	(0.0311)	(0.108)	(0.0991)	(0.0265)
Age2	-0.000247	-0.00173***	-0.00166	-0.00137	-2.87e-05	-0.000781**	-0.00383**	-0.000356	-0.000138
	(0.000963)	(0.000386)	(0.00169)	(0.00106)	(0.000598)	(0.000393)	(0.00163)	(0.00127)	(0.000354)
Married	0.0157	-0.108	-0.257	-0.0164	0.0229	-0.313**	0.0185	0.107	-0.189
	(0.268)	(0.0998)	(0.397)	(0.277)	(0.139)	(0.152)	(0.240)	(0.280)	(0.117)
Secondary	0.355	0.461**	1.734*	4.259***	0.424***	0.294**	0.344	0.0394	0.354***
	(0.584)	(0.228)	(0.899)	(1.150)	(0.145)	(0.131)	(0.269)	(0.387)	(0.100)
Diploma	0.833	1.234***	1.894**	4.002***	0.872***	0.843**	0.548	0.939*	0.230
	(0.509)	(0.227)	(0.735)	(1.203)	(0.196)	(0.370)	(0.429)	(0.534)	(0.233)
Bachelor's degree	1.498**	1.546***	2.555***	4.609***	1.151***	2.033**	0.900	1.652***	Dropped[a]
	(0.553)	(0.226)	(0.821)	(1.189)	(0.305)	(0.926)	(0.977)	(0.520)	
Post-graduate	Dropped[a]	2.122***	3.175**	4.779***	2.267***	Dropped[a]	Dropped[a]	Dropped[a]	0.623
		(0.292)	(1.179)	(1.473)	(0.625)				(0.991)
Post-primary	Dropped[a]	0.815*	1.715	4.305***	0.113	0.765	-0.657	Dropped[a]	0.175
		(0.445)	(1.862)	(1.405)	(0.446)	(0.499)	(1.061)		(0.502)
Tenure	0.0125	0.0154**	0.0565*	0.00228	0.0361***	-0.00600	-0.00737	0.0299	0.00228
	(0.0163)	(0.00631)	(0.0333)	(0.0215)	(0.0135)	(0.00690)	(0.0248)	(0.0227)	(0.00826)
Hours (weekly)	0.00277	0.0118***	0.00621	0.00401	0.00684**	0.0145***	0.0219**	-0.000931	0.00906***
	(0.0118)	(0.00448)	(0.0145)	(0.0100)	(0.00336)	(0.00456)	(0.00988)	(0.00981)	(0.00236)
Firm size	0.0848	0.0726**	0.0677	0.0499	0.0599	0.109***	0.0183	0.101	0.171***
	(0.0523)	(0.0313)	(0.102)	(0.0589)	(0.0432)	(0.0354)	(0.0726)	(0.0774)	(0.0333)
Public sector	0.530	0.585***	0.664	1.189***	0.784***	0.712	0.558	-0.431	0.216
	(0.333)	(0.183)	(0.525)	(0.386)	(0.244)	(0.614)	(0.479)	(0.723)	(0.443)
Private formal sector	0.917	0.400**	0.630	1.395***	0.344*	0.630*	1.138***	-0.678	0.144
	(0.584)	(0.190)	(0.577)	(0.401)	(0.182)	(0.330)	(0.373)	(0.406)	(0.300)
Urban	-0.0781	0.227***	0.130	0.549**	0.281**	0.417**	0.192	0.338	0.132
	(0.237)	(0.0817)	(0.391)	(0.244)	(0.134)	(0.163)	(0.240)	(0.326)	(0.0999)
Christian	-0.0619	-0.252	-0.380	0.258	0.0490	0.651**	-0.557	-0.274	-0.436
	(0.369)	(0.282)	(0.769)	(0.719)	(0.352)	(0.328)	(0.967)	(0.485)	(0.462)
Islamic	Dropped[a]	-0.297	0.248	0.944	0.196	1.295*	-0.191	Dropped[a]	-0.0183
		(0.326)	(0.974)	(0.815)	(0.443)	(0.765)	(1.022)		(0.504)
Union member	0.184	0.431***	0.469	-0.211	-0.485	0.611	-0.803	0.470	0.467
	(0.221)	(0.0907)	(0.524)	(0.255)	(0.320)	(0.479)	(0.704)	(0.947)	(0.432)
Manufacturing		0.256	2.059	1.459	0.225		-0.824	0.174	-0.422
		(0.589)	(1.500)	(1.174)	(0.533)		(0.593)	(1.280)	(0.591)
Tertiary sector 1	Dropped[a]	Dropped[a]	0.376	-0.622	Dropped[a]	Dropped[a]	-0.947	0.00871	0.0773
			(1.007)	(0.958)			(0.575)	(1.479)	(0.587)
Tertiary sector 2	Dropped[a]	0.424	0.302	0.819	-0.288	1.180	-1.474**	0.341	0.278
		(0.617)	(1.045)	(0.855)	(0.381)	(0.992)	(0.653)	(1.471)	(0.186)
Tertiary sector 5	Dropped[a]	0.171	0.0138	1.233	-0.403	-1.249	-0.886	-0.303	0.424***
		(0.346)	(0.764)	(0.778)	(0.387)	(1.746)	(0.624)	(1.319)	(0.150)
Tertiary sector 3	-0.347	0.152	0.110	Dropped[a]	0.509	1.487	-0.512	0.374	0.930*
	(0.931)	(0.602)	(0.720)		(0.477)	(1.390)	(1.069)	(1.252)	(0.519)
Tertiary sector 4	-0.0842	0.292	0.152	1.240	-0.0754	-0.816	-0.982	0.507	0.187
	(0.272)	(0.407)	(0.759)	(0.789)	(0.410)	(1.121)	(0.628)	(0.893)	(0.281)
Tertiary sector 6	Dropped[a]	0.464	-0.324	Dropped[a]	-0.261	Dropped[a]	-0.807	-1.184	0.320**
		(0.928)	(1.318)		(0.444)		(0.882)	(1.341)	(0.136)
Mining/Extractives	Dropped[a]	Dropped[a]	Dropped[a]	Dropped[a]	Dropped[a]	Dropped[a]	Dropped[a]	-0.648	2.536**
								(1.269)	(1.098)
Inverse of Mill's ratio	0.0153	0.544*	0.649	-0.617	-0.177	0.190	0.668	0.194	-0.281
	(0.673)	(0.294)	(1.331)	(0.707)	(0.295)	(0.340)	(0.603)	(0.481)	(0.232)
Constant	7.143***	3.488***	4.853	-0.0649	7.422***	4.217***	3.494	7.917***	7.403***

	(1.823)	(0.815)	(2.905)	(2.684)	(0.983)	(0.758)	(2.150)	(1.902)	(0.692)
Observations	46	511	63	62	436	672	91	40	522
R-squared	0.690	0.481	0.685	0.736	0.326	0.169	0.511	0.816	0.204

Source: Author's calculations (2024) based on KCHS-2021 data. Note: Individuals aged between 15 and 65 years. Standard deviation in brackets, *** p<0.01, ** p<0.05, * p<0.1. Dropped[a] -There were no male respondents with this characteristic in this specific occupation category.

Membership in a labor union is associated with a positive and significant association with wages for both male and female professionals, with a more pronounced effect among women. This highlights the strong bargaining power of Kenyan labor unions, particularly for professional workers. These findings align with earlier studies by Ntuli (2007) and Omanyo (2021), which also reported the positive wage effects of unionization. However, the association is insignificant across all other occupations for both genders, especially in low-skilled roles that dominate Kenya's private informal sectors. This may be because wages in the private sector are often determined through direct employer-employee contracts rather than collective bargaining, which is more common in the public sector (Bhorat et al., 2002).

Using rural residence as the reference category, urban residence has a significant and positive association with wages of women employed as professionals, secretarial/clerical workers, service workers, and skilled agriculture, forestry, and fishery workers. This relationship is particularly strong for women in clerical and secretarial roles, which are closely tied to urbanization. Similarly, urban residence positively and significantly associated with wages of men in professional roles, service work, craft and trade-related occupations, and elementary occupations within the private informal sector. The relationship is most pronounced in elementary occupations, as urbanization fosters greater incentives and employment opportunities. These findings align with Kenya's vibrant informal economy, which accounts for 84% of total employment (KNBS Economic Survey, 2023).

Firm size, measured by the number of employees, positively associated with earnings for both men and women across several occupation categories. For women, this relationship is notable in professional, skilled agriculture, and elementary occupations, while for men, it spans a broader range of occupation categories. These findings align with Antonczyk et al. (2010), who explored the demand-side determinants of wage inequality. Similarly, the number of weekly hours worked in primary occupations is significantly associated with earnings for both genders, though the magnitude and significance of the association vary across occupation categories and gender.

Additionally, tenure—measured as years spent in the current occupation—significantly associated with earnings for men and women in professional, associate professional/technician, and service roles. This supports the positive relationship between tenure and on-the-job training, which enhances productivity and leads to higher earnings (Munasinghe et al., 2008).

Surprisingly, men working as administrators or managers in tertiary sector 1 (electricity, gas, water supply, and construction) experience a significant negative association with wages. Similarly, associate professionals and technicians in tertiary sector 5 (education, health, social work, and other community services) also face a negative association with wages. In contrast, service workers in tertiary sector 5 receive a wage premium. For men in skilled agriculture, forestry, fishery, and plant and machine operations, tertiary sector 6 is associated with a positive wage premium. For women, unskilled and semi-skilled elementary occupations linked to tertiary sectors 3 (transport, storage, communication, and financial intermediation), 5, and 6, as well as mining and extractives, result in a wage premium, with the association being particularly strong in mining and extractives.

Next, the inverse Mills ratio, which accounts for occupational selectivity, is significantly associated with women's earnings in professional occupations. This indicates that the occupational choices of female professionals are not random, underscoring the importance of including a selectivity bias term in pay gap decomposition. This finding aligns with previous studies, confirming the relevance of selectivity bias in wage regression analyses (Ismail et al., 2017; Demoussis et al., 2010; Goy & Johnes, 2012; Omanyo, 2021). However, the inverse Mills ratio is insignificant for all other occupation-specific wage estimations for both men and women, suggesting the absence of a selection problem. Alternatively, this lack of significance may stem from the small sample sizes in the occupation-specific earnings equations.

8.4.4 Multinomial logit occupational attainment model

Table 31 lists the results of the multinomial logit occupational attainment model for male employees, using "craft and trade-related workers" as the reference group. Education is a significant predictor of employment in high-paying occupations for men, including "legislators, administrators, and managers," "professionals," "technicians and associate professionals," "secretarial and clerical workers," and "service and market workers." For women, education is significant only in predicting employment in the "professionals" category (Ismail et al., 2017; Teo, 2003; Orraca et al., 2016). Interestingly, the impact of education is bigger for men than for women. In contrast, higher education levels (e.g., postgraduate) reduce the likelihood of employment for men in low-skilled occupations such as agriculture and elementary roles, while the effect is insignificant for women across all such occupations. These findings align with Kenyan literature, which identifies education as a key determinant of employment and labor market participation (Kabubo-Mariara, 2003; Nyaga, 2010; Agesa et al., 2013; Omanyo, 2021).

Table 31: Multinomial logit results for occupational attainment male model

VARIABLES	Occ1	Occ2	Occ4	Occ5	Occ6	Occ9	Occ3	Occ8
experience	0.0559***	0.0432***	0.0511***	0.00610	0.00513	-0.000430	0.0250***	-0.0101*
	(0.0117)	(0.00717)	(0.0194)	(0.00566)	(0.00509)	(0.00578)	(0.00888)	(0.00587)
Married	0.368	0.491***	0.508	0.142	-0.393***	-0.540***	-0.131	0.126
	(0.335)	(0.186)	(0.580)	(0.128)	(0.116)	(0.127)	(0.203)	(0.129)
Primary	-0.201	-0.665	12.40	0.628	1.209***	1.118***	0.252	0.536
	(1.062)	(0.476)	(805.4)	(0.382)	(0.316)	(0.357)	(0.750)	(0.333)
Secondary	1.337	0.316	13.71	1.117***	0.866***	0.607*	1.206	0.663**
	(1.035)	(0.468)	(805.4)	(0.382)	(0.321)	(0.363)	(0.741)	(0.335)
Diploma	2.679**	3.371***	15.07	1.778***	0.703*	0.353	3.118***	0.829**
	(1.056)	(0.477)	(805.4)	(0.413)	(0.391)	(0.453)	(0.753)	(0.386)
Bachelors	3.787***	4.182***	14.80	1.921***	0.300	0.218	3.376***	0.780
	(1.072)	(0.519)	(805.4)	(0.475)	(0.598)	(0.657)	(0.792)	(0.489)
Postgraduate	3.953**	5.262***	16.57	2.787**	-28.82	-29.48	3.570**	1.184
	(1.599)	(1.121)	(805.4)	(1.159)	(5.013e+06)	(6.959e+06)	(1.429)	(1.453)
Urban	0.0328	-0.985***	0.182	0.320***	-1.873***	-1.061***	-0.158	-0.183
	(0.249)	(0.147)	(0.421)	(0.112)	(0.121)	(0.121)	(0.177)	(0.111)
Household size	0.00441 (0.0518)	-0.011 (0.0302)	0.067 (0.0831)	-0.0616** (0.0238)	-0.00419 (0.0202)	-0.0453* (0.0231)	-0.00174 (0.0368)	.0103 (0.0224)
Constant	-4.848***	-2.559***	-18.32	-1.729***	-0.278	-0.617*	-3.124***	-0.937***
	(1.070)	(0.475)	(805.4)	(0.387)	(0.316)	(0.357)	(0.745)	(0.336)
Observations	4,210	4,210	4,210	4,210	4,210	4,210	4,210	4,210

Source: Author's calculations (2024) based on KCHS-2021 data. Note: Individuals aged between 15 and 65 years. Standard deviation in brackets, *** p<0.01, ** p<0.05, * p<0.1

Potential work experience increases the likelihood of employment in high-paying occupations for both men and women. However, for men, the effect is negative and insignificant in elementary occupations. Surprisingly, potential experience is positively associated with employment in the "plant and machine operators and assemblers" category for women, while the effect is negative for men. And demographic variables show that married individuals are more likely to be employed as "professionals," as indicated by positive and statistically significant coefficients. This effect is significant only for "professionals" among both men and women and it is insignificant across other occupation categories.

Urban residence increases the likelihood of men being employed as "service and sales workers." In contrast, it reduces the probability of both men and women being employed in "professionals," "agriculture," and "elementary occupations." Family size significantly raises the likelihood of women being employed in both the highest-paying occupations, such as "legislators, administrators, and managers," and the lowest-paying "elementary occupations," while it decreases the likelihood of employment for men. These findings partially align with the results of Orraca et al. (2016), Kabubo-Mariara (2003), Nyaga (2010), and Omanyo (2021). Overall, the effects of explanatory variables on occupational attainment vary by gender, indicating that men and women are allocated to occupations differently based on their observed characteristics.

Table 32: Multinomial logit results for occupational attainment female model

VARIABLES	Occ1	Occ2	Occ4	Occ5	Occ6	Occ9	Occ3	Occ8
Experience	0.0919***	0.0626***	0.0689***	0.00367	0.0428***	0.0188	0.0473***	0.0391**
	(0.0193)	(0.0141)	(0.0179)	(0.0134)	(0.0130)	(0.0131)	(0.0181)	(0.0199)
Married	0.265	0.555**	0.369	-0.300	0.157	-0.266	-0.172	-0.546
	(0.397)	(0.258)	(0.357)	(0.236)	(0.235)	(0.233)	(0.348)	(0.396)
Primary	13.38	-2.619**	-3.898**	-0.830	0.200	0.563	-2.017	16.24
	(4,616)	(1.151)	(1.749)	(1.079)	(1.099)	(1.135)	(1.487)	(5,194)
Secondary	15.83	-1.118	-0.709	-0.531	-0.389	-0.000601	-0.868	16.19
	(4,616)	(1.134)	(1.454)	(1.077)	(1.100)	(1.135)	(1.451)	(5,194)
Diploma	17.20	1.930*	1.098	-0.0999	-1.214	-0.611	0.821	16.08
	(4,616)	(1.158)	(1.469)	(1.110)	(1.154)	(1.180)	(1.467)	(5,194)
Bachelors	19.42	3.384**	2.216	0.966	-0.0558	-15.33	2.793	18.16
	(4,616)	(1.504)	(1.776)	(1.475)	(1.561)	(1,092)	(1.758)	(5,194)
Postgraduate	15.52	19.23	17.38	17.08	0.517	16.37	18.71	15.97
	(13,206)	(7,641)	(7,641)	(7,641)	(8,105)	(7,641)	(7,641)	(14,475)
Urban	-0.00514	-1.005***	-0.101	0.247	-2.035***	-0.237	-0.280	0.266
	(0.409)	(0.273)	(0.377)	(0.254)	(0.255)	(0.246)	(0.374)	(0.427)
Household size	0.212***	0.0944	-0.0122	0.00832	0.0898	0.121**	-0.0348	-0.0328
	(0.0807)	(0.0614)	(0.0881)	(0.0572)	(0.0562)	(0.0555)	(0.0861)	(0.0950)
Constant	-18.99	0.593	-0.915	1.992*	1.813	1.035	-0.154	-17.33
	(4,616)	(1.161)	(1.496)	(1.105)	(1.125)	(1.160)	(1.485)	(5,194)
Observations	2,443	2,443	2,443	2,443	2,443	2,443	2,443	2,443

Source: Author's calculations (2024) based on KCHS-2021 data. Note: Individuals aged between 15 and 65 years. Standard deviation in brackets, *** p<0.01, ** p<0.05, * p<0.1

The BMZ decomposition uses the results taken from the multinomial logit model for male occupational attainment to estimate the predicted occupational distribution for women. This approach simulates how women would be distributed across occupations if they followed the same allocation patterns as men i.e., calculation of female predicted distribution using actual female characteristics and the actual male coefficient estimates. The results of the predicted female occupational attainments are presented in Table 33 and Figure 22.

Table 33: Actual and predicted distribution of gender occupational attainment

Occupational category	Men's Actual distribution (P_j^m)	Women's Actual distribution (P_j^f)	Male/ Male + Female	Women's predicted distribution ($\hat{P}_j^f$)
Occ1: Legislators, Administrators, and Managers	0.02	0.02	0.65	0.05
Occ2: Professionals	0.12	0.21	0.47	0.29
Occ3: Technicians and Associate professionals	0.04	0.03	0.74	0.04
Occ4: Secretarial, Clerical services, and related workers	0.01	0.03	0.30	0.22
Occ5: Service workers, shop, and market sales workers	0.14	0.18	0.58	0.23
Occ6: Skilled Agriculture, Forestry, and Fishery workers	0.21	0.28	0.57	0.16
Occ8: Plant and Machine operators and assemblers	0.13	0.02	**0.93**	0.008
Occ9: Elementary Occupations	0.13	0.21	0.51	0.023
Dissimilarity index		**0.369**		**0.0769**

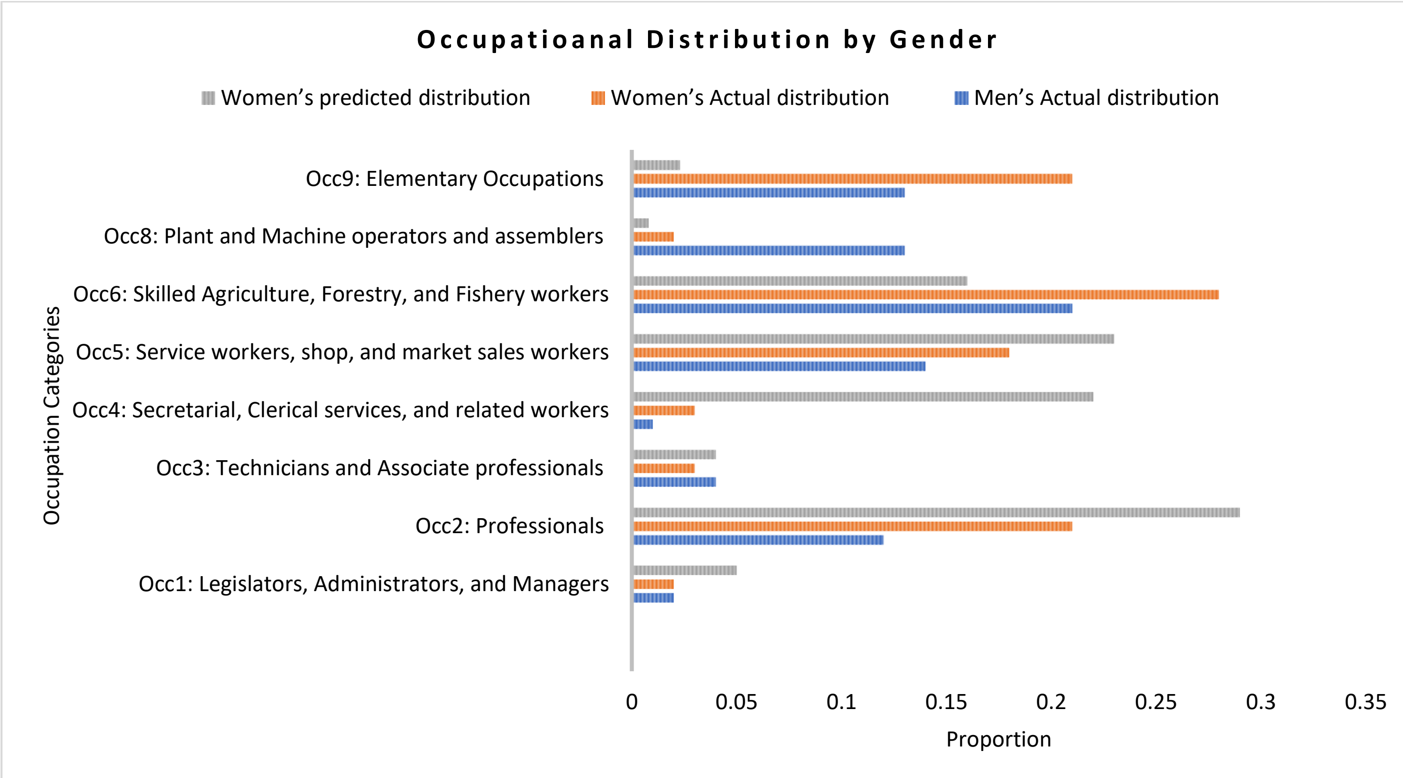
Source: Author's calculations (2024) based on KCHS-2021 data. Note: Occ7 (Craft and trade-related works) is used as a based category in the Multinomial logit model.

Table 33 highlights the disparities between the actual occupational distribution for women (P_j^f) and the predicted distribution ($\hat{P}_j^f$) that would exist in the absence of gender-based occupational discrimination, based on the male allocation rule. The findings reveal that if women are allocated in occupations following the same patterns as men, given their characteristics, a significantly larger proportion would be employed in high-paying occupations such as "legislators/managers/administrators," "professionals," "associate professionals and technicians," "service and sales workers," and "clerical jobs." This indicates that women are currently "under-represented" in these roles. Conversely, women are "over-represented" in lower-paying occupations such as "skilled agriculture, forestry, and fishery" and "elementary occupations." This implies that, given the same occupational choices as men, women would likely shift away from these roles, as they are among the lowest-paying and employ a disproportionately large share of female workers in the informal economy.

When women follow the same occupational allocation rules as men—meaning they have similar occupational attainment patterns—the Duncan index of dissimilarity drops significantly to 7.7%. Similarly, the Duncan index for industrial distribution[26] decreases to 5.8% when women adopt the same industrial sorting function as men. These results align with the findings of Orraca et al. (2016), who also observed a reduction in the dissimilarity index when women's occupational and industrial distributions mirrored those of men.

[26] The Duncan index for industrial distribution using a female predicted distribution is calculated based on 9 industrial categories.

Figure 22: Actual and predicted gender occupational attainment



Source: Author's calculations (2025) based on KCHS-2021 data.

8.4.5 The Brown–Moon–Zoloth decomposition with occupational segregation

Table *34* and Figure 23 present the results of the BMZ earnings decomposition between men and women, disaggregated by occupational segregation and place of residence. The decomposition breaks down the log earnings differential into five components: (1) within-occupation explained wage differentials, (2) within-occupation unexplained wage differentials, (3) between-occupation explained wage differentials, (4) between-occupation unexplained wage differentials, and (5) the sample selection bias term. By analyzing these components, I assess the relative importance of occupational segregation in explaining the earnings gap (Teo, 2003; Goy & Johnes, 2012; Orraca et al., 2016; Bensidoun & Trancart, 2015; Ismail et al., 2017). The goal is to determine whether the significant variations in occupational and industrial distributions, as measured by the Duncan index of dissimilarity, or wage discrimination within the same occupation, are the primary factors driving the observed male-female earnings gap in Kenya.

The results reveal that, when aggregating data across all occupational categories, there is a mean earnings differential of 0.114425[27] log points between male and female employees. This implies that female employees earn approximately 87.9%[28] of men's monthly earnings, indicating a gender pay gap of 12.1% in the Kenyan labor market.

Table 34: BMZ decomposition between men and women by occupational segregation

	Full sample	Percentage share	Urban	Percentage share	Rural	Percentage share
Total log earnings differential	0.1144	100	0.0273	100	0.246	100
	(0.0564)		(0.100)		(0.0675)	
Explained: Differences in mean characteristics						
Within	0.0487	42.6	0.0790	289.4	-0.648	-263.4
	(0.0143)		(0.035)		(0.0145)	
Between	-0.141	-122.9	-0.116	-424.9	-0.105	-42.7
	(0.0100)		(0.0168)		(0.00936)	
Total explained	-0.0923	-80.7	-0.037		-0.753	
Unexplained: Differences in coefficients						
Within	0.157	137.6	0.107	392.0	0.943	383.3
	(0.0366)		(0.0592)		(0.0469)	
Between	0.0438	38.3	-0.0456	-167.0	0.048	19.5
	(0.0392)		(0.0713)		(0.0455)	
Total Unexplained	0.2008	175.5	0.0614		0.991	
Sample selection bias	0.0059	5.2	0.0029	10.6	0.008	3.3
	(0.001)		(0.001)		(0.002)	

Source: Author's calculations (2024) based on KCHS-2021 data. Standard errors are in parentheses. Note: Male coefficients are taken as the non-discriminatory vector. Decomposition is based on the mean values of all variables, the estimated results from occupation-specific regressions, and the predicted occupational attainment in Table 35. Occupation category 7 is a base category in the earnings regression estimations.

Several key insights emerge from the BMZ decomposition results. The gender pay gap is predominantly driven by within-occupation differences between men and women. The combined effect of the within-occupation explained (WE) and unexplained (WU) components, totaling 0.206 log points (180% of the pay gap), indicates that intra-occupation disparities account for the entire observed gender pay differential. In contrast, the sum of the between-occupation explained (BE) and unexplained (BU) components equals −0.0972 log points, reducing the pay gap by 85%, while sample selection bias accounts for only 5% of the differential.

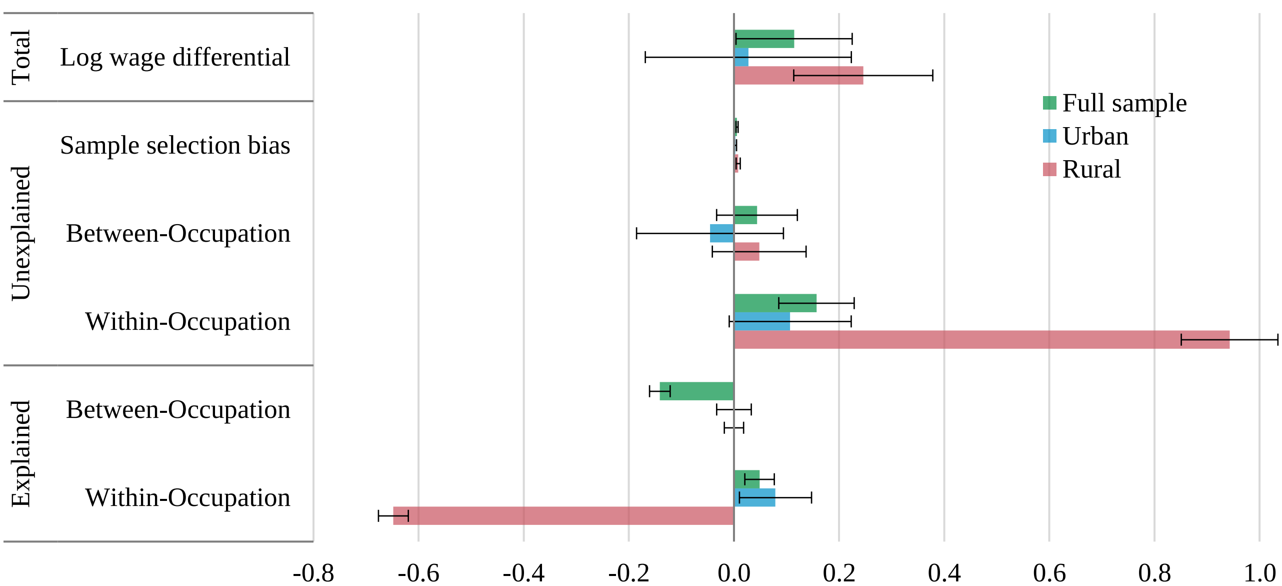
Looking at the two components of the intra-occupational differential reveals a significant heterogeneity in their effects. Specifically, of the 0.206 intra-occupational earning differentials, the WE component, which reflects productivity-related characteristics, contributes 0.0487 log points,

[27] Unweighted data. The BMZ decomposition exercise did not allow the use of sampling weights.
[28] The percentage figure is calculated as $(e^{0.1144} - 1) \times 100$.

accounting for 42.6% of the total pay gap. This suggests that more than two-fifths of the total pay gap stems from gender differences in productivity-related attributes within occupations, which widens the pay gap. The WU component, which captures the unequal treatment of male and female productivity-related characteristics and the distributional share of men and women within occupations, is particularly significant. It rises to 0.157 log points, accounting for approximately 138% of the total gender pay gap, all else being equal. This indicates that the largest portion (138%) of the observed gender pay gap is primarily driven by the unexplained within-occupation wage differences.

These differences likely stem from the unequal treatment of male and female productivity characteristics and potentially from vertical segregation—specifically, disparities in returns to average characteristics within occupations and their distributional/hierarchical shares. In other words, if the returns to average characteristics and workers' distributional shares within occupation were only considered, the gender pay gap would have been even larger than observed. This is because the majority of the within-occupation earnings gap is attributed to the differential treatment of male and female workers, which is interpreted as earnings discrimination. This finding aligns with Ismail et al. (2017) and Orraca et al. (2016), who also found that a significant portion of the gender earnings gap in Malaysia and Mexico, respectively, was due to unexplained factors within occupations.

Figure 23: BMZ Decomposition by gender and occupational segregation



Source: Author's calculations (2024) based on KCHS-2021 data.

The calculated inter-occupational pay differential is -0.0972, which reduces the gender pay gap by 85 percentage points. The negative value indicates that if women were treated the same as men across occupations, their earnings would likely exceed those of male workers, potentially due to unobserved attributes. The explained inter-occupation component is -0.141 log points, accounting for -123% of the observed pay gap, while the unexplained inter-occupation component is 0.0438 log points, representing 38% of the total gender pay gap. The negative sign of the explained inter-occupation component suggests that occupational segregation benefits women, whereas only 38 percentage points of the earnings differential are due to the unequal treatment of men and women across occupations. Notably, the explained inter-occupation component has a greater effect than the unexplained inter-occupation component, meaning the larger negative effect of the explained component is not offset by the unexplained component. This implies that, on average, women are concentrated in better-remunerated occupations, indicating that occupational segregation favors women. However, they still face vertical segregation within occupations, as evidenced by the within-occupation wage differences discussed above.

Although the unexplained inter-occupation component is positive, suggesting it increases the gender pay gap, this effect is outweighed by the explained inter-occupation component. This means that women encounter fewer barriers to entry across occupations compared to within-occupation barriers. If women had the same occupational attainment structure and choices as men, their movement into higher-paying occupations could significantly reduce or even eliminate the GPG. This implies that occupational segregation partially benefits women in the Kenyan labor market. However, caution is warranted. The positive unexplained inter-occupation component suggests that barriers to entry into higher-paying occupations for women still exist, indicating that horizontal occupational segregation cannot be entirely ruled out in the Kenyan labor market. These findings align with the results of Ismail et al. (2017) and Goy and Johnes (2012), who observed similar patterns in Malaysia.

To better understand the reasons behind the "at least" favorable effect of occupational segregation on women, it is necessary to examine the actual and predicted proportions of women's occupational distribution. This analysis highlights occupations with significant disparities. The greatest gender disparity occurs in "elementary occupations" and "agriculture," where the actual proportion of women exceeds the predicted value. Conversely, the occupations where the predicted proportion of women surpasses the actual value are "clerical work," followed by "professionals," "service and trade workers," "legislators, administrators, and managers," and "technicians and associate professionals." Notably, "elementary occupations" and "skilled agriculture, forestry, and fishery" are associated with lower earnings compared to "clerical work," "professionals," "technicians and associate professionals," and "administrators and managers."

This explains why occupational segregation favors female employees: transitioning from low-skilled to higher-skilled occupations is linked to increased earnings. If women had the same occupational attainment structure and choices as men, their earnings would likely rise. Consequently, the significant negative value of the explained inter-occupation component is not offset by the unexplained inter-occupation component, which reflects discriminatory hiring practices in the pre-entry labor market. Overall, the analysis suggests that while occupational segregation benefits women by concentrating them in relatively higher-paying occupations, barriers to entry into certain high-paying roles persist, as indicated by the positive unexplained inter-occupation component.

The combined explained intra-occupation and inter-occupation components (total explained), which account for gender differences in observable characteristics within and between occupations, amount to -0.0923 log points. This suggests that, based on their average observable productivity characteristics, women should earn more than men. In other words, women possess better observable productivity traits, and if these characteristics were equally rewarded, the gender pay gap would decrease by 81%. However, the sum of the unexplained intra-occupation and inter-occupation components, which reflect differences in returns to these observable characteristics, equals 0.2008 log points or 176% of the observed GPG. This indicates that, based on the returns to their average characteristics, the GPG should be larger than what is observed.

Looking at the unexplained components separately, a distinct pattern emerges: the unexplained intra-occupation component is 0.157 log points, while the unexplained inter-occupation component is 0.0438 log points. Interesting, the effect of the BU component is offset by the explained inter-occupation component, whereas the explained intra-occupation component does not offset the unexplained intra-occupation component. This suggests that the pay differential in Kenya is primarily driven by unexplained factors within occupations, such as discriminatory practices (e.g., vertical segregation), which affect the returns to average characteristics. At the same time, women face fewer barriers to entry across occupations. The significant contribution of the total unexplained portion (176%) may indicate weaker legislative controls in the Kenyan labor market to address discriminatory practices and structural factors in both the pre- and post-entry labor market. These findings highlight the persistence of wage discrimination within occupations, despite some favorable effects of occupational segregation for women.

The gender pay gap exhibits a significant variation between urban and rural areas, with rural regions experiencing a much higher gap at 0.246 log points compared to 0.0273 log points in urban areas. In metropolitan regions, the combined explained intra-occupation and inter-occupation components amount to -0.037 log points, or -136% of the GPG. This implies that, based on their average productivity characteristics, women in urban areas possess favorable traits that reduce the pay gap. However, the unexplained intra-occupation and inter-occupation components total 0.0614 log points, or 225% of the GPG, suggesting that the gap would be larger if returns to their average characteristics and occupational structures were fully considered. In rural areas, the combined explained intra-occupation and inter-occupation components account for -0.753 log points, or -306% of the GPG. This indicates that most of the pay gap in rural areas would be eliminated if differences in average characteristics within and between occupations were addressed. However, the unexplained intra-occupation and inter-occupation components total 0.991 log points, or 403% of the GPG, implying that the gap would have been even more pronounced based on the returns to their average characteristics.

These results indicate that the impact of "explained factors" (intra- and inter-occupation) in reducing the GPG is more significant in rural areas, while the effect of "unexplained factors" is less pronounced in urban areas. Notably, the urban inter-occupation component is -0.0456 log points, indicating that women in urban areas are, on average, concentrated in better-remunerated occupations. At the same time, the positive intra-occupation component in both rural and urban regions suggests that vertical segregation—unequal treatment within occupations—is a key driver of the pay differential. Overall, these findings highlight the persistent role of discriminatory practices and structural barriers, particularly in rural areas, where unexplained factors contribute substantially to the GPG.

In the BMZ decomposition, the correction term is treated separately, and it is not included in the explained or unexplained components. This approach involves delineating the components of the wage decomposition—WE, WU, BE, and BU—to represent the wage offer gap[29]. The wage offer gap refers to the wage a worker randomly drawn from the population would receive if selected for a specific occupational category (Gyourko & Tracy, 1988; Orraca et al., 2016). The selection term differential, which accounts for sample selection bias, is 0.0059 log points (5%) for the entire sample, 0.0029 log points (10.6%) for urban areas, and 0.008 log points (3.3%) for rural areas. These selection correction terms are favorable, indicating that the wage offer gap is slightly smaller than the total wage gap due to selectivity bias in occupational choice. The findings on the contribution of sample selection bias in this study appear more realistic compared to those of Goy and Johnes (2012) and Ismail et al. (2017), who reported that sample selection bias accounted for 63.1% and 35.8% of the total wage differential, respectively.

8.4.6 Discussion of the results

The decomposition results, contextualized within Kenya's labor market dynamics underscores the multifaceted drivers of the gender pay gap. A stark rural-urban divide persists, with rural areas recording a GPG of 27.9% compared to 2.8% in urban regions. This disparity reflects systemic inequities tied to informal employment dominance, climate vulnerability, and weak labor protections. In rural Kenya, where 81% of non-agricultural and 97% of agricultural workers operate informally, women are disproportionately concentrated in low-paying sectors like agriculture and elementary occupations. While decomposition's "explained" factors (e.g., productivity-related characteristics) suggest that addressing observable traits could theoretically reduce the rural GPG by 306%, the overwhelming "unexplained" component (403%) highlights entrenched discrimination and vertical segregation. These findings align with Kenya's informal economy, where lax enforcement of labor laws and limited unionization—particularly in Export Processing Zones—perpetuate wage disparities. Only 16% of workers are unionized, and collective bargaining agreements cover just 3.7% of total employment, leaving women with minimal leverage to challenge discriminatory practices.

In urban areas, the smaller GPG masks persistent vertical segregation within occupations. For instance, women in education and healthcare earn less than men despite comparable representation, a trend exacerbated by declining real wages in public sectors (5.2% drop in 2022). Even in male-dominated industries like manufacturing (77.1% male) and mining (87.2% male),

[29] We do not calculate the wage offer gap in this analysis.

women face barriers to upward mobility, reflecting decomposition's finding that intra-occupation discrimination drives 138% of the GPG. This is compounded by the rise of gig economy jobs, where platform workers—many of whom are women—lack job security, benefits, and union representation. Digital platforms classify workers as independent contractors, evading labor regulations and stifling collective bargaining, further entrenching wage gaps.

Structural challenges are amplified by climate-induced displacement and migration. Over 2.4 million Kenyans displaced by climate disasters since 2008 often enter informal work, where women face heightened exploitation. Migration to urban areas or abroad exposes women to precarious conditions, such as restrictive visa systems that limit labor rights. These pressures align with BMZ's observation that rural women's earnings would theoretically surpass men's if not for systemic barriers like occupational segregation and wage discrimination.

Legislative and institutional gaps further exacerbate inequities. Despite progressive policies like the 2010 Constitution and ratified ILO conventions, weak enforcement of anti-discrimination laws and under-resourced labor inspections (1 inspector per 147,000 workers) fail to curb exploitative practices. Social protection coverage remains low (9% of the population), and the absence of unemployment benefits leaves women disproportionately vulnerable during economic shocks. Nominal wage increases (e.g., 11% in 2022) are eroded by inflation (7.7%), particularly in essentials like food (13.1% inflation) and transport (8.1% inflation), disproportionately affecting women in low-wage roles.

Education and skills mismatch also play a role. While BMZ results attribute part of the GPG to productivity traits, 20% of Kenyan youth are not in education, employment, or training, with women facing higher rates (24%). Despite educational gains, systemic barriers—such as limited formal job creation and gendered unpaid care responsibilities—prevent women from translating skills into equitable wages. Horizontal segregation further limits opportunities, as women remain underrepresented in high-paying STEM fields and overrepresented in informal care roles (e.g., 66.2% of domestic workers are women).

8.4.7 Sensitivity of the results

The BMZ decomposition method frequently relies on aggregated occupational and industrial classifications due to methodological constraints like insufficient sample sizes in niche occupations. However, this broad categorization risks obscuring critical variations in earnings within occupational and industrial groups, as it masks wage disparities and structural heterogeneity that exist even within seemingly homogeneous categories. This limitation raises concerns about the precision of decomposition outcomes, as earnings differentials attributable to specific professions or industries may be diluted or misrepresented. Nevertheless, I will conduct a sensitivity analyses by performing earnings decompositions at broader levels of occupational and industrial aggregation.

Table 35[30] details results under broader levels of occupational and industrial aggregation, revealing contrasting effects of classification granularity on explained and unexplained wage gap components. For occupational segregation, reducing the classification from 9 to 6 categories resulted in a decline in the explained wage gap component (WE and BE) from −0.0923 to −0.109 log points. Concurrently, the unexplained components—(BU) and (WU)—increased marginally, while (WE) slightly decreased. This suggests that coarser occupational classifications obscure structural wage determinants, amplifying unexplained disparities while diminishing the explanatory power of workplace and between-group factors. Conversely, industrial segregation analysis demonstrates a divergent pattern. Aggregating industries from 9 to 5 categories increased the explained component (WE + BE) from −0.0507 to 0.0345 log points, signaling improved explanatory capacity under broader classifications. The total unexplained component (WU + BU) decreased from 0.178 to 0.092 log points, with BE rising by 0.0074 and WE by 0.0778 log points, while BU and WU declined by 0.05 and 0.0106 log points, respectively. These results highlight the fact that industrial wage disparities are more sensitive to aggregation, as broader categories better capture systemic sectoral inequalities.

Table 35: Sensitivity of BMZ decomposition of log earnings differential between men and women to different levels of occupational and industrial segregation

	Occupational Segregation				Industrial Segregation			
	WE	BE	WU	BU	WE	BE	WU	BU
9 categories	0.0487	-0.141	0.157	0.0438	0.0422	-0.0929	0.214	-0.0614
	(0.0143)	(0.0100)	(0.0366)	(0.0392)	(0.0144)	(0.00841)	(0.0365)	(0.0437)
6 occupation and 5 industry categories	0.0291	-0.138	0.161	0.0664	0.120	-0.0855	0.164	-0.0720
	(0.0147)	(0.00813)	(0.0359)	(0.0281)	(0.0154)	(.00599)	(0.0354)	(0.0257)

Source: Author's calculations (2024) based on KCHS-2021 data. Standard errors in parentheses. Note: 9 occupational and industrial categories; 6 categories for occupation and 5 categories for industry.

[30] Given the smaller cell size in some occupations and industries with nine categories, we were forced to increase their cell size by re-grouping some categories so as to have a broader category (6 and 5 occupation and industry categories, respectively).

Occupational segregation exhibits limited sensitivity to classification granularity: reducing the number of occupational categories fails to meaningfully augment the proportion of the wage gap explained by structural factors. In contrast, industrial segregation demonstrates greater sensitivity to aggregation levels, with the explained component exhibiting marked variability across industry classifications. A persistent pattern emerges in the direction of segregation effects: for industrial segregation, the negative sign of the (BU) term suggests that sectoral distribution does not inherently widen the gender pay gap in Kenya and it may marginally benefit women.

8.5 Chapter conclusion

Here, I sought to critically examine the structural drivers of Kenya's gender pay gap, with a specific focus on the role of occupational segregation. The primary objectives were twofold: first, to quantify the extent of occupational and industrial segregation using the Duncan dissimilarity index; second, to disentangle intra-occupational pay disparities from inter-occupational inequities, employing the BMZ decomposition framework. The results revealed a multifaceted interplay of factors underpinning Kenya's GPG. Occupational segregation, as measured by the Duncan index, underscored significant gender imbalances, with 37% of women (men) needing to transition occupations to achieve parity with men's distribution. However, the decomposition results demonstrated that intra-occupational disparities—particularly the *unexplained* component reflecting differential returns to equivalent qualifications—dominated the GPG, accounting for 138% of the aggregate gap. This finding highlights the prevalence of vertical segregation and wage-setting discrimination within occupations, where women face systemic undervaluation despite comparable roles. In contrast, inter-occupational segregation paradoxically *reduced* the GPG by 85%, as women's concentration in certain higher-paying sectors partially offset disparities.

Nevertheless, rural-urban divides starkly shaped outcomes: rural areas exhibited a GPG nearly nine times larger than urban centers (27.8% vs. 2.8%), driven by informality, climate vulnerability, and weaker labor protections. In synthesizing these findings, the outcome means that Kenya's GPG is not merely a function of occupational sorting, but a manifestation of systemic inequities embedded in labor market architectures. Policy interventions must prioritize dismantling vertical segregation through the stringent enforcement of equal pay legislation, enhanced workplace equity audits, and targeted upskilling programs to bridge human capital gaps.

9. SUMMARY, CONCLUSION, AND RECOMMENDATIONS

In this thesis, I explored gender pay gaps and occupational segregation in Kenya's labor market using both conventional and innovative estimation methods. I sought to uncover the sources and extent of these disparities, addressing key questions such as: Is the public sector more financially rewarding? What factors determine earnings differences between men and women across sectors and age groups? How do gender pay gaps vary between formal (public and private) and informal sectors, different age cohorts (15-34 vs. 35-65 years), and education levels? Additionally, the thesis examined divergencies in occupational, industrial, and sectoral distributions between men and women, and whether these contribute to women's earnings disadvantages in Kenya. Now, the key findings are summarized, linking gender pay gaps to employment sectors, age, education, and occupational segregation. I conclude with actionable recommendations and identify possible areas for future research.

9.1 Summary

The gender pay gap—defined as the difference in gross earnings between men and women in the same job, occupation, and industry (Metcalf, 2009)—is a significant social injustice and a reflection of global inequality. It remains a pressing issue in both developing and developed economies (*see* Blau & Kahn, 2017). However, progress has been made in recent decades, with earnings gaps narrowing (Blau & Kahn, 2017; Kolesnikova & Liu, 2011). This improvement is largely due to women's increased educational attainment, greater work experience, and shifts in occupational preferences.

Classical economic theories attribute the gender pay gap primarily to two factors: qualifications and discrimination (*see* Becker, 1957, 1964). The human capital model posits that higher qualifications, achieved through investments in education and vocational training, lead to increased earnings for both men and women (Grybaitė, 2006; Lips, 2013; Blau & Kahn, 2007). Although women have made significant strides in educational attainment in recent years (Botsch, 2015), their returns on investment in qualifications remain lower than those of men. And work experience—such as years in the labor market and job tenure—plays a key role in sustaining gender-based earnings disparities (Sierminska et al., 2010).

Women frequently bear the burden of the "second shift," balancing unpaid domestic labor with paid market work due to traditional gender roles. This dual responsibility often results in fragmented careers during their most productive years, leading them to choose occupations that are more forgiving of career interruptions (Alvarez et al., 2006; Gupta & Ash, 2008; Moyser, 2019). These interruptions reduce productivity and availability, contributing to lower earnings (Blau et al., 2006; Bryan & Sanz, 2007). While both market and domestic labor are essential for societal reproduction, only market labor is economically rewarded. As a result, women's extensive unpaid work generates significant societal benefits, but they are often compensated less than men. Additionally, women may self-select into lower-paying occupations compared to those typically dominated by men (Miller, 2009). Despite advancements in policies, shifting social norms, and women's increased investment in human capital—such as education, work experience, and broader occupational choices—the gender pay gap persists.

With this context, this thesis contributes to the discourse by examining the sources of the gender pay gap and the impact of occupational segregation on gender pay disparities in Kenya's labor market. In Chapter One, I established the rationale for the thesis by exploring explanations for the gender pay gap and the actuality and justification of the topic, outlining objectives, research questions, and hypotheses. Chapter two contextualized Kenya's labor market within its historical evolution, legal frameworks, and institutional structures. Chapter Three provided the theoretical framework for understanding the sources of gender earnings disparities. Chapter Four introduced the foundational Oaxaca-Blinder decomposition technique, a key method for analyzing gender earnings inequality. The empirical investigations and decomposition methods used in chapters six, seven, and eight are adaptations of this established approach.

In Chapter Five, I introduced data concepts, defined key terms, outlined variables, and presented descriptive statistics from the three empirical studies. The findings tell us that women generally experience less favorable employment outcomes than men, with lower overall employment rates for women. The descriptive findings reveal significant gender disparities in Kenya's labor market, shaped by employment sectors, education, and structural inequalities. Women face lower employment rates (73.56% vs. 80.40% for men) and they are disproportionately engaged in unpaid home labor (12.44% of women vs. 4.59% of men), reflecting entrenched gender roles. Wage employment is dominated by the informal sector (73.1% of men and 65.1% of women), with men more likely to secure formal roles in public or private sectors. While women show higher educational attainment at advanced levels, a persistent gap favors men with bachelor's degrees, especially among younger cohorts. Occupational segregation is stark: highly educated women are more likely to hold professional roles (61% vs. 44% of men), but low-educated individuals—especially women—are relegated to low-skilled jobs (only 4.5% of low-educated women work as professionals).

Earnings disparities further underscore these inequities. Women earn 89.1% of men's unadjusted average wages, with gaps widening in the private informal sector (71.9% of men's earnings) and among low-educated workers (0.3538 log points vs. 0.1163 for highly educated). The pay gap follows distinct patterns: a U-shaped curve for low-educated workers (peaking at the bottom/top of the distribution) and an inverted U-shape for highly educated workers (widest at the median). Kernel density analyses highlight a "sticky floor" effect, with low-educated women concentrated in low-wage roles. Structural factors—such as the informal sector's dominance (85% of employment), limited wage regulation, and cultural norms—perpetuate these gaps. Younger workers face informal sector precarity, while older workers benefit from formal, unionized roles.

In Chapter Six, the sources and extent of the gender pay gap in Kenya's formal (public and private) and informal sectors, as well as across different age groups were investigated, using comprehensive, nationally representative KCHS-2021 data. The thesis hypothesizes that covariates determining earnings may influence gender-based earnings differently, with certain factors having a more significant impact on the GPG depending on the sector and age cohort. Furthermore, it posits that gender pay discrimination, including glass ceilings and sticky floors, is less prevalent in the public sector compared to the informal sector, given that sectoral choice is often an endogenous, predetermined process. To address these questions, I employed multiple estimation models for earnings equations, including OLS, BFG, and Heckman selection models, while accounting for double selection bias and endogeneity issues related to wage employment and sectoral choice. The analysis decomposes the gender pay gap in both sectors and across age cohorts (15-34 years and 35 years and older) at the mean and various points along the earnings distribution. This was achieved using the standard Oaxaca decomposition, Neumark, and reweighted Oaxaca-RIF decomposition methods.

At the conditional mean level, the GPG in Kenya is starkest in the informal sector, where women earn 41.8% less than men, compared to a 6.4% gap in the public sector. This disparity underscores the role of informality, which accounts for 81% of non-agricultural employment and

97% of agricultural work. Women in informal sectors—such as agriculture, domestic work, and petty trade—face a "sticky floor" effect, trapped in low-productivity jobs with minimal social protection. Weak enforcement of labor laws, under-resourced labor inspectors (1 per 147,000 workers), and limited unionization (14% in Export Processing Zones) exacerbate structural discrimination. In contrast, the public sector's relatively lower GPG reflects institutional efforts to promote gender parity through standardized pay scales and affirmative action in recruitment. However, biases persist at higher deciles, where male-dominated political appointments for managerial roles perpetuate inequality.

The GPG widens with age, peaking at 16.6% for older workers (35+ years) compared to 9.5% for younger cohorts (15–34 years). For older women, cumulative disadvantages—such as occupational segregation into informal caregiving or subsistence farming and unequal returns to experience—drive this gap. Younger women, while facing a narrower GPG, confront emerging barriers like gig economy precarity and skills mismatches. Notably, 20% of Kenyan youth are NEET (not in education, employment, or training), with women disproportionately hindered by childcare responsibilities and limited access to vocational training.

In the main, the wage structural effect—systemic undervaluation of women's productivity—dominates the GPG, accounting for 70.1% to 113.4% of the gap at the aggregate mean. In the private formal sector, structural biases are pronounced at the lower deciles (50.2%s), driven by cyclical wage discrimination and employer discretion. Conversely, the private informal sector's structural effect peaks at higher deciles (46.2%), reflecting unregulated working hours and the absence of collective bargaining. For older workers (35+ years), structural biases dominate, stemming from cumulative discrimination, where older women face unequal returns to potential experience and occupational segregation into low-paying roles such as informal caregiving or subsistence farming, compounded by limited retraining opportunities. In contrast, younger workers (15–34 years) experience structural effects most acutely at the lower deciles of the earnings distribution, driven by emerging labor market challenges like gig economy precarity and skills mismatches.

Education, while reducing the GPG through composition effects (−13%), is undermined by structural undervaluation. For instance, in the private informal sector, gender differences in educational attainment widen the gap by 3.2% at the bottom decile, as men's higher educational endowments are disproportionately rewarded. And while education reduces the GPG through composition effects for both cohorts, its impact is undermined by structural biases, particularly in the informal sector, where men's educational advantages are disproportionately rewarded. These dynamics highlight how age intersects with systemic wage-setting inequities to perpetuate Kenya's gender pay disparities.

Kenya's labor market is characterized by weak alignment between education and labor needs. Women constitute 50% of tertiary graduates but remain overrepresented in low-growth sectors like agriculture, where credentials hold little value. TVET programs, though enrolling 643,000 students in 2023, offer only 500–600 annual apprenticeships, limiting pathways to formal employment. Thus, as Kenya continues to pursue foreign investment, particularly in EPZs, it prioritizes cost-cutting over equitable practices, relegating women to low-skilled roles in apparel manufacturing. Therefore, the persistence of Kenya's GPG is not merely a statistical artifact but a reflection of systemic failures. Addressing it requires targeted interventions: formalizing informal enterprises, strengthening labor law enforcement, expanding social protections (e.g., National Social Security Fund coverage), and aligning education with market demands. While the public sector offers a blueprint for progress through unionization and standardized pay, dismantling structural biases in wage determination remains critical across all sectors and age cohorts.

In Chapter Seven, I analyzed the gender pay gap across different education strata's in Kenya, utilizing data from the KCHS-2021. The dataset comprised 1,500 highly educated and 5,153 low-educated workers. The thesis sought to test the hypothesis that highly educated women face a pronounced glass ceiling effect, whereas low-educated women are more likely to experience a sticky floor effect. Here, I estimated the determinants of earnings while controlling sample selection bias separately for highly educated and low-educated men and women. Then I decomposed the gender pay gap across the entire earnings distribution using the Machado and Mata (2005) decomposition method.

The gender pay gap in Kenya's labor market manifests itself distinctly across education levels, shaped by systemic undervaluation of women's productivity and entrenched institutional inequities. Drawing on decomposition analyses and contextual insights from Kenya's labor dynamics, this chapter showed how structural barriers and discriminatory practices disproportionately penalize both low- and highly educated women, albeit through different mechanisms. The findings revealed that low-educated women face severe earnings penalties, with losses relative to men ranging from 25% to 66.7%. The GPG peaks in median quantiles, driven primarily by structural effects—systemic undervaluation of their productivity characteristics. Even when possessing comparable skills to men, their concentration in Kenya's informal economy (81% of non-agricultural employment) traps them in low-productivity sectors like retail, domestic work, and small-scale agriculture. Here, informal roles lack standardized wages, union representation (only 3.7% coverage), and labor protections, exacerbating discrimination. The TVET programs, though expanding, fail to bridge these gaps due to fragmented curricula and limited industry linkages. Despite reforms, theoretical training dominates, leaving women—86% of informal workers—ill-equipped for upward mobility. Counterfactual decomposition showed that remunerating low-educated women's characteristics at male rates could reduce disparities, but weak labor inspection and informality make this potential solution currently unrealizable.

Highly educated women encounter a pronounced *glass ceiling*, with unexplained pay gaps peaking at the 70th percentile of the earnings distribution. Despite constituting 50% of managerial positions, vertical occupational segregation persists in formal sectors like education and public administration, where cultural biases and discriminatory promotion practices hinder advancement. Even with identical qualifications, women face earnings penalties of 8.3–28.9%, most evident at the top quantiles. Kenya's digital economy typically illustrates these challenges. While sectors like ICT offer opportunities, women in platform-based roles are often classified as independent contractors, excluded from labor protections. Algorithmic management and precarious contracts in the gig economy exacerbate wage discrimination, underscoring the disconnect between advanced skills and equitable remuneration.

The intersection of age, education, and sectoral stratification further elucidates the multifaceted nature of Kenya's GPG. While low-educated women face entrenched *sticky floors* exacerbated by informality and age-related precarity, highly educated women confront escalating *glass ceilings* in both formal and informal sectors. Kenya's labor market institutions perpetuate these disparities. Weak enforcement of progressive laws—such as low maternity leave coverage (6.3%) and negligible paternity leave uptake—reinforces gendered care burdens. The brain drain in critical sectors like healthcare intensifies competition, enabling discriminatory practices. For highly educated women, inconsistent adherence to collective bargaining agreements (e.g., 44% coverage in education) fails to counteract biases in wage negotiations. Based on the findings, mitigating Kenya's GPG demands multifaceted interventions. Strengthening TVET-industry linkages, formalizing informal enterprises, and expanding social protection are critical for low-educated women. For highly educated women, enforcing anti-discrimination laws, promoting gender-responsive labor policies, and regulating the digital economy's contractual practices are essential. Both cohorts require systemic shifts to dismantle the structural and cultural biases that undervalue women's labor, ensuring productivity gains translate into equitable outcomes across all education levels.

In Chapter Eight, the thesis explored the role of occupational and industrial segregation in driving gender pay disparities in Kenya, emphasizing that occupational choices and structures are endogenously determined rather than exogenous. Utilizing data from the KCHS-2021, disaggregated into 2,903 urban and 3,750 rural workers, and applying the BMZ decomposition method, the thesis found that employment patterns in Kenya are highly concentrated by industry, occupation, and sector. The results of the Duncan dissimilarity index revealed that achieving gender-equitable employment distribution would require approximately 37% of women (men) to change occupations, 9% to shift sectors, and 30% to switch industries. These findings underscore the significant role of structural segregation in perpetuating gender pay differentials.

Moreover, the gender pay gap in Kenya exhibits stark disparities between rural and urban areas, shaped by structural inequities and systemic undervaluation of women's labor. The decomposition results revealed a rural GPG of 27.9 percentage compared to a significantly smaller urban gap of 2.9 percentage. This divergence underscores the interplay of occupational segregation, informal employment, and institutional weaknesses in Kenya's labor market. Rural Kenya's GPG is driven by pervasive informality, with 81% of non-agricultural and 97% of agricultural workers in informal roles. Women are disproportionately concentrated in low-paying sectors like subsistence farming and elementary occupations, where wages are unregulated and labor protections virtually absent. The result means that while addressing observable productivity characteristics (e.g., education, experience) could theoretically eliminate 306% of the rural GPG, the overwhelming "unexplained" component (403%) reflects entrenched earnings discrimination and vertical segregation. In other words, if women's average productivity traits were equally rewarded like their male counterparts, the gender pay gap would be eliminated. However, the gap widens when considering the returns to these observable characteristics and the occupational distribution of men and women, accounting for 403% of the total GPG in rural areas. This highlights the systemic undervaluation of women's productivity in Kenya's rural labor market. For instance, rural women face unequal returns to their characteristics, compounded by weak unionization (only 3.7% are covered by collective agreements) and under-resourced labor inspections (1 inspector per 147,000 workers). Climate-induced displacement exacerbates these challenges, as 2.4 million Kenyans have been displaced since 2008—many of them females—enter informal work with heightened exploitation risks.

Urban regions exhibit a smaller GPG (2.9%) but reveal persistent vertical segregation within occupations. Women in urban areas seem to exhibit superior productivity-related characteristics within and across occupations. Observable factors reduce the GPG more significantly in rural areas (-306%) than in urban regions (-136%). In contrast, the impact of returns to these factors, occupational structures, and discriminatory practices is less pronounced in urban areas (225%) compared to rural areas (403%). Urban areas showed a negative *inter-occupation* unexplained component, indicating fewer barriers for women accessing higher-paying jobs. However, the positive *intra-occupation* unexplained component in both regions pointed to wage structural effects and vertical occupational segregation as key drivers of pay disparities. Women in sectors like education and healthcare earn less than men despite comparable representation, reflecting *intra-occupation* discrimination. While urban women are concentrated in better-remunerated occupations (evidenced by a negative *inter-occupation* unexplained component), they face vertical occupational barriers in high-paying roles like STEM fields and managerial positions.

Based on the rural-urban findings, Kenya's labor market dynamics are marked by legislative inadequacies and enforcement failures. Despite progressive policies like the 2010 Constitution and ratified ILO conventions, weak enforcement of anti-discrimination laws and limited social protections (covering only 9% of the population) perpetuate inequities. Rural women, for example, earn below gazetted minimum wages in agriculture (KSh 10,107 monthly in 2022), which fail to offset rising living costs. Urban-rural migration and international labor migration expose women to restrictive visa systems and precarious contracts, aligning with the finding that systemic barriers negate women's theoretical earnings advantages. Thus, addressing Kenya's GPG requires targeted interventions tailored to rural and urban contexts. Formalizing informal jobs, expanding unionization, and enforcing labor laws are critical in rural areas. Urban reforms should focus on regulating gig economy practices and dismantling vertical segregation. Nationally, aligning TVET programs with market needs, expanding social protections, and mitigating climate-induced displacement are essential to translating women's productivity gains into equitable wages.

9.2 Conclusion

In this thesis, I investigated the sources and magnitude of the gender pay gap in Kenya's formal (public and private) and informal sectors, as well as across different age cohorts. And I assessed whether highly educated women confront a significant "*glass ceiling*" effect while low-educated women experience a "*sticky floor*" effect. Then, by accounting for differences in occupational and industrial structures and distributions between men and women, I evaluated the role of occupational and industrial segregation in driving gender pay disparities in Kenya. Drawing on the findings and discussions presented, I concluded by addressing the relevant research objectives and hypotheses, providing insights into the systemic and structural factors underpinning the GPG in Kenya's labor market.

Regarding the first hypothesis, this thesis examined whether earnings disparities between men and women in Kenya align with the human capital model and how these dynamics vary across sectors and age cohorts. The findings confirmed that women earn significantly less than men, with the gender pay gap most pronounced in the informal sector—particularly the informal economy, where women earn 41.8% less than men—compared to a narrower 6.4% gap in the public sector and 8.3% in the private formal sector. While the formal sector demonstrates relative progress through standardized pay scales and affirmative action, systemic undervaluation of women's productivity persists, driven by structural inequities and discriminatory practices. Age further stratifies the gender pay gap: Older workers (35+ years) experience a gap of 16.6%, nearly double that of younger cohorts (9.5%). Older women, despite accumulating better productivity characteristics over time, face cumulative discrimination, including occupational segregation into informal caregiving and unequal returns to experience. Younger women, though encountering a narrower gap, grapple with emerging barriers like gig economy precarity and skills mismatches, compounded by childcare responsibilities and limited access to vocational training. Sadly, 20% of Kenyan youth are "NEET", with women disproportionately affected.

The human capital elements mostly explains these disparities. Education, a key component, reduces the gender pay gap via composition effects, as women increasingly match or surpass men in educational attainment due to government-led gender equity initiatives. However, these gains are undermined by wage structural effects—discriminatory returns to productivity traits—which dominate the gender pay gap, accounting for 70.1% to 113.4% of the aggregate gap. This highlights the systemic undervaluation of women's productivity traits and observable qualifications, aligning with labor market discrimination theories—statistical and taste-based discrimination—and the enduring influence of occupational segregation in perpetuating pay disparities.

While wage structural effects are more pronounced in the informal sector, their significant presence in the public sector underscores institutional biases favoring men, particularly in senior leadership roles often tied to political appointments that predominantly benefit male employees. In the informal sector, women face a "sticky floor," trapped in low-productivity roles like agriculture and domestic work with minimal social protections. Weak enforcement of labor laws, under-resourced labor inspections, and limited unionization exacerbate these challenges. Conversely, the public sector's institutional frameworks mitigate some disparities but fail to address biases in top managerial roles, often reserved for men through political appointments and structural factors. Furthermore, in the private formal sector, structural biases at lower deciles reflect employer discretion and cyclical wage discrimination. In contrast, the informal sector's structural effects peak at higher deciles, highlighting unregulated working conditions and absent collective bargaining. Moreover, demographic factors—such as marital status and regional disparities—and job-related attributes like firm size and union affiliation further entrench gender inequities in Kenya's labor market.

The thesis concluded by stating that addressing Kenya's gender pay gap across sectors of employment and age cohorts necessitates a multifaceted approach to dismantle systemic barriers. Critical measures include formalizing informal employment sectors, rigorously enforcing labor laws, and expanding social protections such as NSSF coverage. Aligning TVET programs with labor market demands and implementing regulations to ensure fair practices in the gig economy can mitigate emerging inequalities. While the formal sector serves as a model through unionization and standardized pay structures, equitable wage policies must be uniformly adopted across all sectors, including informal economy. Ultimately, bridging the GPG requires comprehensive reforms that translate women's productivity into equitable remuneration, fostering a labor market grounded in fairness and inclusivity.

Regarding the hypothesis that highly educated women in Kenya confront a significant "*glass ceiling*" effect, while low-educated women experience a "*sticky floor*" effect, the results support this hypothesis. The findings underscore how structural inequities in labor markets interact with educational attainment to shape gendered earning trajectories. For low-educated women, the gender pay gap is most pronounced in the lower to median quantiles of the earnings distribution, potentially driven by horizontal occupational segregation and concentration in low-productivity informal roles such as domestic work and small-scale agriculture. The "*sticky floor*" effect is evident at lower quantiles, where women face significant earnings penalties despite possessing comparable productivity traits to men. Counterfactual analysis revealed that if low-educated women retained their characteristics but were remunerated at male rates, the GPG would decline. However, weak enforcement of labor laws, limited unionization, and fragmented TVET programs—which fail to align skills with market demands—erode these potential gains. Notably, the narrowing GPG at the top quantiles among low-educated workers aligns with Kenya's minimum wage policies, suggesting unionized roles offer some protection, albeit insufficient to overcome systemic undervaluation.

Highly educated women, conversely, confront a pronounced "*glass ceiling*" effect, with the GPG widening at higher quantiles. Potentially, vertical occupational segregation within formal sectors like education and public administration limits their access to leadership roles, despite constituting 50% of managerial positions. Remarkably, 70% of this gap stems from unexplained factors—discriminatory returns to qualifications and biased promotion practices—highlighting institutional failures. Even in Kenya's burgeoning digital economy, platform-based roles (e.g., ICT and gig work) classify women as independent contractors, denying them labor protections and perpetuating opaque pay structures. Counterfactual scenarios showed that remunerating highly educated women at male rates would invert the GPG at upper quantiles, favoring women, but systemic barriers would still persist. The intersection of age, education, and sectoral stratification further reveals the complex nature of Kenya's GPG. While low-educated women face entrenched *sticky floors* exacerbated by informality and age-related precarity, highly educated women confront escalating *glass ceilings* in both formal and informal sectors.

In the main, structural drivers underpin these disparities. Kenya's informal economy traps low-educated women in unregulated jobs with minimal social protections. For highly educated women, despite progressive labor laws, inconsistent enforcement of maternity leave (6.3% coverage) and paternity leave exacerbates care-related career interruptions. And the brain drain in critical sectors like healthcare intensifies competition, allowing discriminatory practices. Furthermore, TVET reforms, though expanding enrollment, still prioritize theoretical training over apprenticeships (500–600 annually), limiting pathways to formal employment for women. Thus, Kenya's GPG by education stratification reflects not just human capital disparities but systemic failures in labor market structures and institutional enforcement.

Here, the thesis concluded that dismantling these barriers requires a dual focus that translate women's educational and productivity gains into equitable remuneration, fostering inclusive growth across all education levels. For low-educated women, formalizing informal jobs, enforcing minimum wage standards, and strengthening TVET-industry linkages are critical. For highly educated women, regulating digital labor platforms, enforcing anti-discrimination laws, and promoting gender-responsive promotions in formal sectors are essential. Nationally, expanding social protections (e.g., NSSF coverage) and addressing gendered occupational segregation through legislative reforms can help bridge disparities.

Regarding the third thesis hypothesis, the findings affirmed that occupational status and structures play a pivotal role in explaining Kenya's gender pay gap. Gender employment distributions across industries, occupations, and sectors are markedly concentrated, reinforcing systemic disparities. The result showed that if Kenyan women (men) had parity in occupational opportunities and choices, a significant shift toward higher-paying roles—such as legislators, managers, professionals, associate professionals, technicians, service and sales workers, and clerical positions—would most likely occur. However, women remain underrepresented in these sectors, a disparity attributed to employer discrimination and unobserved barriers restricting their access. Conversely, women are disproportionately overrepresented in low-paying occupations, including skilled agriculture, forestry, fishery, and elementary roles. This implies that equitable occupational access would reduce women's concentration in these low-wage sectors, highlighting the need to dismantle structural and discriminatory practices to achieve gender parity in earnings.

The decomposition results revealed that *intra-occupation* disparities—driven by unequal returns to productivity characteristics and occupational structures between men and women—account for the largest portion of the gender pay gap, underscoring pervasive vertical segregation. Rural areas exhibited a pronounced GPG, nearly nine times higher than urban areas. This rural-urban chasm stems from Kenya's informal economy, where non-agricultural and agricultural workers lack formal protection. Rural women, concentrated in low-productivity sectors like subsistence farming, face compounded disadvantages. Here, the explained factors (e.g., productivity traits) could theoretically reduce the entire rural GPG, but *unexplained* components—reflecting discrimination and vertical segregation within occupations—dominate. In other words, if rural women's average productivity traits were equally rewarded, the gender pay gap would be eliminated. However, the gap widens when considering the returns to these observable characteristics and the occupational distribution of men and women. This could be explained by weak unionization and under-resourced labor inspections perpetuating structural inequities, leaving rural women vulnerable to exploitative practices.

In urban areas the gender pay gap is narrower but revealed persistent vertical segregation within occupations. Urban areas show a negative *inter-occupation* unexplained component, indicating fewer barriers for women accessing higher-paying jobs. In other words, while urban women are concentrated in better-remunerated occupations, they face vertical barriers in high-paying roles like STEM fields. The positive *intra-occupation* unexplained component point to wage structural effects and vertical occupational segregation as key drivers of pay disparities. Women in sectors like education and healthcare earn less than men despite comparable representation. The finding that *intra-occupation* discrimination drives largest share of the urban GPG, highlights how digital labor markets amplify wage inequities in urban regions.

Altogether, the gender pay gap in Kenya is deeply intertwined with occupational segregation and structural inequities, with stark disparities evident between rural and urban labor markets. Although women remain fairly represented in high-paying roles, they face structural barriers for upward mobility largely due to discrimination and unobserved barriers, and they are overrepresented in low-paying sectors. This occupational divide is compounded by systemic factors, including rural informality, weak labor protection and institutional policies enforcements, and discriminatory wage practices, which collectively perpetuate earnings disparities.

9.3 Policy Implications

This thesis provided insights into the structural and institutional drivers of gender pay disparities, supported by rigorous empirical analyses in chapters six, seven, and eight. These findings equip policymakers with actionable evidence on the sources of earnings inequalities, enabling the design of targeted interventions to advance workplace equity. Based on the findings and conclusions, several important policy implications can be inferred.

1) **Strengthen Labor Institutions and Inspections:** Increase the number of trained labor inspectors from the current ratio of 1 inspector per 147,000 workers and allocate budgetary resources to enforce minimum wage compliance, occupational safety, and anti-discrimination laws in informal sectors. Enforce penalties for wage discrimination, particularly in EPZs and informal sectors. Introduce mandatory wage transparency audits in formal sectors (public/private) and enforce penalties for non-compliance with the Employment Act 2007, such as fines for employers violating equal pay provisions.
2) **Promote Social Dialogue and Unionization:** Integrate gender-responsive clauses into collective agreements, as seen in the Kenya National Union of Teachers' successful negotiation of maternity benefits. Legally recognize informal worker associations and facilitate collective bargaining for fair wages, which calls for amending the Labor Institutions Act to include informal sector representation.
3) **Extend Social Protections**: Utilize the Informal Sector Transformation Unit to extend social protections (e.g., National Social Security Fund) and National Hospital Insurance Fund) to cover informal workers (e.g., *Jua Kali* artisans, gig workers) through subsidized contributions (e.g., tiered payment plans) particularly women in sectors like retail, domestic work, and agriculture. This would mitigate vulnerabilities linked to informality, such as lack of pensions and healthcare.
4) **Reform TVET programs to bridge skills mismatch**: Revise TVET curricula to address sectoral demands, reducing skills mismatches that perpetuate undervaluation of women's qualifications. Partner with industries (e.g., ICT, renewable energy, agribusiness) to redesign TVET curricula, prioritizing competency-based assessments over theoretical

training to address the mismatch between training and labor market needs Require TVET institutions to allocate 30% of coursework to apprenticeships, ensuring at least 5,000 annual placements (up from 500–600) for women in high-demand sectors. Also, offer scholarships and childcare stipends to women enrolling in STEM fields to counter occupational segregation.

5) **Dismantle Vertical Segregation in Formal Sectors**

   Amend the Salaries and Remuneration Commission Act to mandate gender parity in senior leadership roles (e.g., CEOs, board members) across public and private institutions. Introduce quotas requiring 40% female representation in managerial positions by 2030, with annual audits published by the National Gender and Equality Commission (NGEC). Adopt the Kenya National Union of Teachers (KNUT) model, which successfully negotiated maternity benefits into collective agreements, for replication in healthcare and manufacturing sectors.

6) **Certify Informal Skills**: Implement Recognition of Prior Learning programs through the National Industrial Training Authority to validate skills of informal workers, enabling transitions to formal employment.

7) **Expand Parental Leave Policies to Redistribute Caregiving Responsibilities**: Enact legislation to increase maternity leave coverage beyond the current 6.3% to 50% of formal sector workers by 2030 and introduce *paid* paternity leave to redistribute caregiving burdens and retain women in the workforce reducing career interruptions. Subsidize employer costs for parental leave through tax incentives, modeled as Unemployment Insurance Fund (UIF).

8) **Regulate Platform Work:** Reclassify gig workers as employees (e.g., ride-hailing drivers, freelancers) as employees under the Labor Relations Act 2007, guaranteeing minimum wages, overtime pay, and unionization rights and collective bargaining rights. Establish a Digital Labor Task Force under the MLSP to audit algorithmic wage-setting practices in platforms like Uber and Bolt, ensuring transparency and fairness.

9.4 Suggestions for future research

A key limitation of this thesis lies in its cross-sectional analysis of gender pay gaps and occupational segregation, which provides only a snapshot of Kenya's labor market dynamics. To build on these findings, future research should adopt longitudinal and intersectional approaches to see how these disparities evolve over time and across demographic dimensions. Critical avenues for investigation include:

1) **Sectoral Evolution of the GPG:** Track longitudinal trends in formal sector disparities, assessing in particular whether gender equity policies (e.g., Affirmative Action) have mitigated structural biases in public sector leadership or exacerbated private sector inequities. The thesis found that while the public sector offers relatively favorable conditions for women, men still dominate top managerial roles—a dynamic requiring temporal analysis to evaluate policy efficacy.
2) **Lifecycle Dynamics of Earnings Disparities:** Investigate how the GPG shifts across women's career trajectories. While older women in the public sector benefit from accumulated productivity traits, future studies should examine whether these gains erode due to career interruptions (e.g., childcare) or retirement transitions, which disproportionately affect women's earnings.
3) **Educational Reforms and Occupational Barriers:** Evaluate the impact of Kenya's Competency-Based Curriculum (CBC) and expanded TVET programs on reducing the "sticky floor" effect for low-educated women and dismantling vertical segregation for highly educated women. Such a study could clarify whether skill-based reforms have altered occupational mobility or reinforced existing hierarchies.
4) **Urbanization and Digital Economy Impact:** Analyze how rural-urban migration and digital labor platforms (e.g., remote work) reshape occupational access. The thesis found rural women encounter severe penalties due to vertical/horizontal segregation, while urban women benefit marginally from inter-occupation mobility. Future work could assess whether digital opportunities mitigate rural exclusion or perpetuate urban-centric inequities.
5) **Long-Term Policy Efficacy:** Systematically evaluate labor interventions like minimum wage adjustments and union advocacy, especially their sustained impact on low-educated workers. While Kenya's strengthened wage policies narrowed gaps in unionized roles,

horizontal segregation persists—a trend require a decade-long assessment to provide scalable solutions.

6) **Intersectional Frameworks:** Integrate factors such as ethnicity and parenthood into GPG analyses. For instance, ascertain how rural-urban divides intersect with ethnic marginalization or caregiving responsibilities to compound earnings penalties for specific subgroups.
7) **Advanced Methodologies and Data Innovations:** Utilize emerging datasets (e.g., National Social Security Fund records) for cohort-based wage trajectory analyses. Pair this with causal inference methods or machine learning techniques to disentangle discrimination, occupational sorting, and policy effects, moving beyond descriptive decomposition to identify actionable incentives for change.

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APPENDICES

Appendix I.

Table A1: Decomposing gender pay gap by percentiles and age cohorts: The RIF-Oaxaca detailed decomposition.

Age 35+	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	10%	20%	30%	40%	50%	60%	70%	80%	90%
Pure composition effect									
Potential experience	-0.00761	-0.0310	0.00182	0.0303	0.0182	0.0190	0.0117	0.00493	0.00972
	(0.117)	(0.0426)	(0.0268)	(0.0253)	(0.0246)	(0.0245)	(0.0247)	(0.0278)	(0.0337)
Education	-0.0802***	-0.0181*	-0.0248***	-0.0289***	-0.0541***	-0.0524***	-0.0615***	-0.0823***	-0.0946***
	(0.0287)	(0.00949)	(0.00756)	(0.00785)	(0.0123)	(0.0120)	(0.0137)	(0.0180)	(0.0208)
Industrial effects	-0.0275	-0.0171	-0.00937	-0.0101	-0.0111	-0.00819	-0.00593	-0.00562	-0.00338
	(0.0181)	(0.0106)	(0.00589)	(0.00628)	(0.00683)	(0.00517)	(0.00390)	(0.00383)	(0.00298)
Occupational effects	-0.0156	0.000761	0.00502	0.00993**	0.0141**	0.0134**	0.00872**	-0.00352	-0.0110**
	(0.0137)	(0.00482)	(0.00356)	(0.00455)	(0.00579)	(0.00559)	(0.00422)	(0.00343)	(0.00553)
Sectoral effects	-0.0530*	-0.0375***	-0.0278***	-0.0400***	-0.0388***	-0.0457***	-0.0533***	-0.0443***	-0.0317***
	(0.0274)	(0.0128)	(0.00893)	(0.0113)	(0.0110)	(0.0126)	(0.0144)	(0.0126)	(0.0106)
Marital effects	-0.00122	-0.000522	-0.000347	-0.00152	-0.00162	-0.00185	-0.00304	-0.00265	-0.00138
	(0.00345)	(0.00139)	(0.000910)	(0.00335)	(0.00358)	(0.00409)	(0.00667)	(0.00583)	(0.00309)
Religion	-0.00224	-0.000275	-0.000140	0.000497	0.000422	0.000470	0.000381	0.000556	0.000693
	(0.00706)	(0.000970)	(0.000526)	(0.00156)	(0.00133)	(0.00148)	(0.00121)	(0.00175)	(0.00217)
Regional effects	-0.0215	-0.00849	-0.00862	-0.00745	-0.00619	-0.00649	-0.00414	-0.00243	-0.00167
	(0.0203)	(0.00800)	(0.00800)	(0.00692)	(0.00579)	(0.00606)	(0.00395)	(0.00252)	(0.00208)
Firm characteristics	-0.0751***	-0.0254**	-0.0200***	-0.0212***	-0.0171***	-0.0127**	-0.0149**	-0.0209***	-0.0248***
	(0.0284)	(0.00997)	(0.00746)	(0.00772)	(0.00647)	(0.00522)	(0.00586)	(0.00778)	(0.00929)
Hours of work	0.0275	0.0215*	0.0143*	0.00984*	0.00344	0.00220	-0.00350	-0.00708	-0.0138*
	(0.0175)	(0.0127)	(0.00847)	(0.00591)	(0.00250)	(0.00197)	(0.00254)	(0.00445)	(0.00828)
Unionization	-0.000250	-0.00368	-0.00490	-0.00445	-0.00833*	-0.0125**	-0.0163**	-0.0248**	-0.0222**
	(0.0102)	(0.00408)	(0.00322)	(0.00293)	(0.00427)	(0.00592)	(0.00750)	(0.0112)	(0.0102)
Selectivity bias term	0.0254	-0.0264*	-0.00511	-0.00903	-0.0147*	-0.0275***	-0.0712***	-0.0840***	-0.0747***
	(0.0410)	(0.0151)	(0.00941)	(0.00865)	(0.00870)	(0.00915)	(0.0124)	(0.0144)	(0.0151)
Pure wage structural effect									
Potential experience	0.583	-0.465	0.000966	0.202	0.923	1.844*	-1.003	0.769	0.709
	(4.378)	(1.227)	(0.911)	(0.896)	(0.929)	(0.976)	(0.968)	(0.955)	(1.166)
Education	-0.418	0.000138	0.123	0.260**	0.201*	-0.183	0.166	-0.103	-0.352**
	(0.526)	(0.154)	(0.115)	(0.113)	(0.117)	(0.124)	(0.122)	(0.120)	(0.147)
Industrial effects	-0.508	-0.0768	0.101	0.120	0.00680	0.210**	0.200**	0.0947	0.0210
	(0.408)	(0.120)	(0.0890)	(0.0875)	(0.0902)	(0.0944)	(0.0940)	(0.0929)	(0.114)
Occupational effects	0.224	-0.0533	0.240*	0.385***	0.561***	0.430***	-0.106	-0.595***	-0.0816
	(0.615)	(0.190)	(0.141)	(0.139)	(0.147)	(0.156)	(0.153)	(0.150)	(0.182)
Sectoral effects	0.0643	-0.157	-0.104	-0.197	0.0343	0.710***	0.914***	0.0456	-0.369
	(1.0966)	(0.305)	(0.226)	(0.223)	(0.233)	(0.246)	(0.243)	(0.239)	(0.291)
Marital effects	-0.350	-0.162	-0.276***	-0.353***	-0.348***	-0.409***	-0.309***	-0.167	-0.161
	(0.497)	(0.143)	(0.107)	(0.105)	(0.106)	(0.109)	(0.110)	(0.110)	(0.135)
Religion	1.223*	0.485**	0.263*	0.345**	0.141	0.264	0.198	0.0840	-0.0979
	(0.725)	(0.199)	(0.147)	(0.146)	(0.154)	(0.164)	(0.160)	(0.157)	(0.190)
Regional effects	0.163	0.185	-0.0146	-0.415***	-0.391**	-0.688***	-0.495***	-0.197	-0.283
	(0.755)	(0.212)	(0.157)	(0.155)	(0.161)	(0.169)	(0.167)	(0.165)	(0.201)
Firm characteristics	0.764	0.334**	0.104	-0.170	-0.739***	-0.353***	-0.0763	-0.0855	0.297*
	(0.538)	(0.165)	(0.122)	(0.121)	(0.126)	(0.132)	(0.131)	(0.129)	(0.157)
Hours of work	0.431	0.278	-0.000896	-0.234*	-0.400***	-0.351**	-0.171	-0.0287	-0.308*
	(0.670)	(0.187)	(0.139)	(0.137)	(0.143)	(0.151)	(0.149)	(0.146)	(0.178)
Unionization	0.0466	0.0256	0.0143	0.0282	0.0285	0.0160	-0.0332	-0.0932***	-0.0361
	(0.108)	(0.0307)	(0.0228)	(0.0225)	(0.0234)	(0.0245)	(0.0244)	(0.0248)	(0.0293)
Selectivity bias term	0.453	-0.206	-0.203	-0.0872	-0.373*	-1.042***	-1.010***	-0.764***	-0.775***
	(1.062)	(0.302)	(0.225)	(0.221)	(0.226)	(0.235)	(0.236)	(0.234)	(0.286)
Intercept	-1.7002	-0.889	-0.443	0.195	0 1.386**	2.010***	2.038***	1.914***	2.110***
	(2.131)	(0.604)	(0 .451)	(0. .444)	(0.459)	(0.483)	(0.482)	(0.469)	(0.569)
No. of observations	3,239	3,239	3,239	3,239	3,239	3,239	3,239	3,239	3,239
Age 15-34 years									

Pure composition effect									
Potential experience	0.0875	0.00242	0.00231	0.00288	0.00971**	0.00747*	0.0218***	0.0140***	0.0146**
	(0.102)	(0.00994)	(0.00538)	(0.00454)	(0.00467)	(0.00454)	(0.00577)	(0.00536)	(0.00670)
Education	-0.0584**	-0.0264***	-0.0211***	-0.0195***	-0.0209***	-0.0184***	-0.0186***	-0.0223***	-0.0398***
	(0.0270)	(0.00972)	(0.00639)	(0.00570)	(0.00589)	(0.00542)	(0.00544)	(0.00633)	(0.0104)
Industrial effects	0.00187	0.00147	0.000924	0.000828	0.000945	0.000843	0.000366	9.07e-05	0.00165
	(0.00452)	(0.00303)	(0.00188)	(0.00168)	(0.00190)	(0.00171)	(0.000808)	(0.000440)	(0.00329)
Occupational effects	-0.0128	-0.0116*	-0.00323	0.00139	0.00371	0.00363	-0.000579	0.00630*	0.00197
	(0.0146)	(0.00630)	(0.00270)	(0.00209)	(0.00241)	(0.00239)	(0.00193)	(0.00323)	(0.00286)
Sectoral effects	-0.0324	-0.00766	-0.0104**	-0.0111**	-0.0124**	-0.0189**	-0.0215**	-0.0271**	-0.0282**
	(0.0210)	(0.00619)	(0.00504)	(0.00502)	(0.00543)	(0.00782)	(0.00879)	(0.0110)	(0.0116)
Marital effects	-0.00277	0.00387	0.00584	0.00831**	0.00725**	0.00820**	0.00790**	0.0122**	0.00728*
	(0.0165)	(0.00545)	(0.00355)	(0.00386)	(0.00350)	(0.00377)	(0.00367)	(0.00510)	(0.00422)
Religion	0.00686	0.000370	0.000579	0.00108	0.00188	0.00200	0.00162	0.00152	0.000888
	(0.00880)	(0.00147)	(0.001000)	(0.00136)	(0.00218)	(0.00230)	(0.00191)	(0.00183)	(0.00132)
Regional effects	0.0435	0.0207	0.0151	0.0160	0.0124	0.0128	0.0113	0.00633	0.00176
	(0.0289)	(0.0134)	(0.00972)	(0.0103)	(0.00796)	(0.00821)	(0.00727)	(0.00422)	(0.00200)
Firm characteristics	-0.0135	-0.00786	-0.00518	-0.00529	-0.00603	-0.00499	-0.00410	-0.00224	-0.00302
	(0.0180)	(0.0102)	(0.00672)	(0.00685)	(0.00780)	(0.00647)	(0.00532)	(0.00297)	(0.00400)
Hours of work	0.0343	0.0174	0.0104*	0.00578	0.00255	-0.000590	-0.00122	-0.00291	-0.00737
	(0.0218)	(0.0106)	(0.00631)	(0.00361)	(0.00191)	(0.00123)	(0.00137)	(0.00214)	(0.00465)
Unionization	-0.000338	0.000199	0.000226	0.000243	0.000522	0.000388	0.000556	0.00150	0.00218
	(0.00183)	(0.000890)	(0.000930)	(0.000987)	(0.00209)	(0.00156)	(0.00223)	(0.00600)	(0.00871)
Selectivity bias term	-0.0512	-0.0287*	0.0111	0.00569	0.00138	-0.00386	-0.00476	-0.0310***	-0.0327***
	(0.0512)	(0.0167)	(0.00896)	(0.00750)	(0.00719)	(0.00719)	(0.00711)	(0.00849)	(0.0108)
Pure wage structural effect									
Potential experience	1.641	-0.117	-0.0665	-0.0313	-0.0180	-0.00733	-0.000239	-0.0639	-0.0993
	(1.138)	(0.0979)	(0.0571)	(0.0520)	(0.0533)	(0.0546)	(0.0527)	(0.0573)	(0.0846)
Education	-1.547***	-0.110	0.0171	-0.0276	-0.135	-0.315***	-0.296***	-0.207**	-0.334**
	(0.598)	(0.155)	(0.0914)	(0.0844)	(0.0872)	(0.0894)	(0.0859)	(0.0931)	(0.141)
Industrial effects	-2.426***	-0.269*	-0.0902	0.0965	0.286***	0.290***	0.175**	0.170**	0.125
	(0.525)	(0.145)	(0.0846)	(0.0770)	(0.0791)	(0.0810)	(0.0781)	(0.0849)	(0.125)
Occupational effects	-1.855**	-0.529***	-0.317***	-0.0283	-0.0473	-0.263**	-0.299***	-0.0583	0.0110
	(0.736)	(0.180)	(0.107)	(0.100)	(0.104)	(0.107)	(0.102)	(0.111)	(0.171)
Sectoral effects	1.619	0.639*	0.0355	0.0980	0.459**	0.216	0.231	-0.191	-0.510*
	(1.259)	(0.346)	(0.202)	(0.184)	(0.189)	(0.193)	(0.187)	(0.203)	(0.300)
Marital effects	-0.913*	-0.368***	-0.304***	-0.244***	-0.263***	-0.298***	-0.324***	-0.324***	-0.278**
	(0.504)	(0.135)	(0.0790)	(0.0723)	(0.0744)	(0.0762)	(0.0734)	(0.0798)	(0.119)
Religion	-0.572	-0.188	-0.101	-0.113	-0.0984	-0.161	-0.141	-0.257**	-0.780***
	(0.795)	(0.180)	(0.108)	(0.104)	(0.109)	(0.112)	(0.106)	(0.115)	(0.182)
Regional effects	-0.681	0.386	0.304**	0.270**	-0.145	-0.123	0.0163	-0.240*	-0.382*
	(0.913)	(0.242)	(0.142)	(0.130)	(0.134)	(0.138)	(0.132)	(0.144)	(0.216)
Firm characteristics	-0.795	0.321*	0.127	0.0699	0.0637	0.000573	0.207**	0.0543	-0.327**
	(0.639)	(0.169)	(0.0994)	(0.0914)	(0.0942)	(0.0965)	(0.0929)	(0.101)	(0.151)
Hours of work	-1.572**	-0.149	-0.151	-0.279***	-0.338***	-0.302***	-0.151	0.0224	0.0885
	(0.734)	(0.193)	(0.114)	(0.105)	(0.108)	(0.111)	(0.106)	(0.115)	(0.173)
Unionization	0.0526	0.0235	0.00622	0.00617	0.0105	0.000526	-0.00802	0.0183*	-0.0482***
	(0.0643)	(0.0169)	(0.00983)	(0.00908)	(0.00943)	(0.00958)	(0.00925)	(0.0102)	(0.0161)
Selectivity bias term	-0.311	-0.450	0.117	0.0557	-0.0603	-0.115	0.0513	-0.104	-0.404
	(1.114)	(0.312)	(0.182)	(0.165)	(0.169)	(0.173)	(0.167)	(0.182)	(0.267)
Intercept	11.338***	1.775**	0 .718*	0.524	1.111**	1.628***	1.138***	1.336***	2.617***
	(2.290)	(0.617)	(0 .361)	(0.332)	(0.344)	(0.354)	(0.343)	(0.372)	(0.548)
No. of observations	3.414	3.414	3.414	3.414	3.414	3.414	3.414	3.414	3.414

Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The dependent variable is the estimated RIF at the respective decile of the log earnings. The gender wage gap is the difference between log male earnings and log female earnings. Sampling weights are used in the estimations. Standard errors reported in parentheses are robust to heteroskedasticity and clustered residuals within households. The reweighting factors are estimated using the logit model. *** p<0.01, ** p<0.05, * p<0.1.

Appendix II.

Table A2: Decomposing gender pay gap by percentiles and sectors of employment: The RIF-Oaxaca detailed decomposition.

Public sector	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	10%	20%	30%	40%	50%	60%	70%	80%	90%
Pure composition effect									
Potential experience	0.00736	0.0158	0.0503***	0.0576***	0.0635***	0.0705***	0.0788***	0.0753***	0.0793***
	(0.0185)	(0.0177)	(0.0192)	(0.0192)	(0.0175)	(0.0178)	(0.0189)	(0.0184)	(0.0219)
Education	-0.0817***	-0.100***	-0.0856***	-0.0752***	-0.0712***	-0.0707***	-0.0642***	-0.0565***	-0.0701***
	(0.0249)	(0.0285)	(0.0249)	(0.0223)	(0.0202)	(0.0197)	(0.0180)	(0.0163)	(0.0210)
Industrial effects	0.00543	0.00567	0.0101	0.00901	0.00415	0.00277	-0.00296	-0.00324	-0.00708
	(0.00604)	(0.00595)	(0.00807)	(0.00732)	(0.00422)	(0.00338)	(0.00336)	(0.00350)	(0.00620)
Occupational effects	0.00545	0.0166	-0.00507	-0.00474	-0.00781	-0.00462	-0.00625	-0.00579	-0.00734
	(0.00653)	(0.0118)	(0.00588)	(0.00551)	(0.00617)	(0.00439)	(0.00507)	(0.00486)	(0.00650)
Marital effects	0.0129	0.0278*	0.0163	0.00604	-0.00372	-0.00869	-0.00573	0.000604	0.0131
	(0.0108)	(0.0145)	(0.0107)	(0.00824)	(0.00637)	(0.00659)	(0.00582)	(0.00538)	(0.00936)
Religion	0.00117	-0.000778	-0.00135	-0.000730	-0.00121	-0.00165	0.000510	0.000115	0.00275
	(0.00404)	(0.00376)	(0.00367)	(0.00331)	(0.00278)	(0.00273)	(0.00225)	(0.00222)	(0.00401)
Regional effects	0.000230	0.000295	0.000343	0.000138	0.000136	0.000150	8.12e-05	0.000121	0.000244
	(0.00633)	(0.00813)	(0.00944)	(0.00382)	(0.00376)	(0.00414)	(0.00224)	(0.00333)	(0.00673)
Firm characteristics	-0.000687	-0.00112	-0.000764	-0.000618	-0.000880	-0.000601	-0.000666	-0.000942	-0.00112
	(0.00750)	(0.0123)	(0.00835)	(0.00675)	(0.00962)	(0.00657)	(0.00727)	(0.0103)	(0.0122)
Hours of work	-0.0218*	-0.0386**	-0.0470***	-0.0260**	-0.0111	-0.00963	-0.0172**	-0.00539	-0.0119
	(0.0124)	(0.0158)	(0.0177)	(0.0119)	(0.00758)	(0.00676)	(0.00799)	(0.00606)	(0.00915)
Unionization	-0.00501	-0.00686	-0.0115	-0.0102	-0.00860	-0.00683	-0.00599	-0.00546	-0.00161
	(0.00863)	(0.0116)	(0.0193)	(0.0171)	(0.0144)	(0.0115)	(0.0101)	(0.00920)	(0.00316)
Selectivity bias term	-0.00877	-0.101***	-0.0603*	-0.0847***	-0.0292	-0.0378*	-0.0213	-0.0332*	-0.0309
	(0.0347)	(0.0346)	(0.0315)	(0.0303)	(0.0230)	(0.0208)	(0.0197)	(0.0201)	(0.0284)
Pure wage structural effect									
Potential experience	-0.112	-0.0620	-0.0318	-0.0521	0.0156	0.0650	0.220**	0.0944	0.240*
	(0.161)	(0.143)	(0.130)	(0.108)	(0.0924)	(0.0875)	(0.0888)	(0.0956)	(0.126)
Education	0.161	0.446	0.376	0.310	0.112	-0.159	-0.615***	-0.499**	-0.323
	(0.354)	(0.312)	(0.283)	(0.236)	(0.202)	(0.192)	(0.195)	(0.210)	(0.275)
Industrial effects	0.185	0.273	0.288	0.456	-0.155	-0.122	-0.115	-0.205	-0.321
	(0.438)	(0.379)	(0.344)	(0.291)	(0.250)	(0.237)	(0.243)	(0.262)	(0.339)
Occupational effects	-0.0115	-0.0399	-0.0272	0.197*	-0.0137	-0.0714	0.0496	0.00927	-0.0311
	(0.159)	(0.137)	(0.124)	(0.106)	(0.0909)	(0.0862)	(0.0884)	(0.0952)	(0.123)
Marital effects	-0.0763	-0.326**	-0.0722	-0.127	-0.0984	-0.240***	-0.0344	-0.120	-0.147
	(0.150)	(0.135)	(0.122)	(0.100)	(0.0859)	(0.0815)	(0.0818)	(0.0884)	(0.117)
Religion	-0.471	-0.469*	-0.324	-0.185	-0.323*	-0.204	0.0876	-0.168	0.0479
	(0.297)	(0.260)	(0.235)	(0.198)	(0.170)	(0.161)	(0.165)	(0.177)	(0.231)
Regional effects	-0.481	-0.584**	-0.748***	-0.541**	0.170	0.0672	-0.0156	-0.0747	0.194
	(0.333)	(0.293)	(0.266)	(0.222)	(0.191)	(0.180)	(0.183)	(0.198)	(0.259)
Firm characteristics	-0.269	0.0217	-0.418	-0.206	-0.174	-0.218	-0.229	-0.172	-0.0643
	(0.363)	(0.319)	(0.289)	(0.242)	(0.208)	(0.197)	(0.201)	(0.216)	(0.282)
Hours of work	-0.555	-0.755**	-0.572*	-0.383	-0.550**	-0.322	-0.495**	-0.0532	-0.316
	(0.414)	(0.353)	(0.320)	(0.275)	(0.237)	(0.225)	(0.233)	(0.250)	(0.319)
Unionization	-0.0600	-0.0737	0.00844	-0.0574	-0.155***	-0.112***	-0.0202	-0.0191	-0.0884
	(0.0767)	(0.0677)	(0.0614)	(0.0512)	(0.0447)	(0.0420)	(0.0422)	(0.0455)	(0.0599)
Selectivity bias term	-0.115	-0.602	-0.472	-0.591*	-0.516*	-0.311	-0.321	-0.723***	-0.550
	(0.466)	(0.417)	(0.379)	(0.311)	(0.267)	(0.252)	(0.254)	(0.275)	(0.364)
Intercept	2.0956*	2.54367**	2.326**	1.493*	1.990**	1.837**	1.674**	2.0674***	1.479*
	(1.0185)	(0.899)	(0.816)	(0.679)	(0.583)	(0.552)	(0.560)	(0.604)	(0.793)
No. of observations	1,229	1,229	1,229	1,229	1,229	1,229	1,229	1,229	1,229
Private formal sector									
Pure composition effect									
Potential experience	0.0133	0.0362*	0.0404***	0.0469***	0.0534***	0.0441***	0.0377**	0.107***	0.0949***
	(0.0215)	(0.0192)	(0.0154)	(0.0163)	(0.0169)	(0.0165)	(0.0174)	(0.0296)	(0.0321)
Education	-0.0819**	-0.102***	-0.107***	-0.120***	-0.142***	-0.160***	-0.235***	-0.368***	-0.426***
	(0.0370)	(0.0328)	(0.0267)	(0.0282)	(0.0300)	(0.0326)	(0.0426)	(0.0631)	(0.0750)
Industrial effects	-0.00280	-0.00461	-0.000809	0.000181	-0.000141	0.00662	0.00639	0.00678	0.00775

	(0.00495)	(0.00708)	(0.00211)	(0.00182)	(0.00178)	(0.00978)	(0.00949)	(0.0102)	(0.0118)
Occupational effects	-0.00452	0.00180	0.00391	0.00723	0.00919	0.00932	0.00953	0.0120	0.00367
	(0.00637)	(0.00381)	(0.00500)	(0.00846)	(0.0106)	(0.0107)	(0.0111)	(0.0140)	(0.00629)
Marital effects	0.0156	0.0132	0.0184*	0.0327**	0.0254**	0.0220*	0.0193	0.0149	-0.000567
	(0.0146)	(0.0122)	(0.0106)	(0.0144)	(0.0123)	(0.0119)	(0.0121)	(0.0143)	(0.0167)
Religion	-0.00102	-0.000308	-3.78e-06	-0.000344	-0.000442	-0.000169	0.000790	0.00184	0.00456
	(0.00491)	(0.00163)	(0.000537)	(0.00172)	(0.00216)	(0.000985)	(0.00379)	(0.00876)	(0.0216)
Regional effects	-0.000532	-0.000810	-0.000519	-0.000302	-0.000309	-0.000336	-0.000111	3.07e-06	0.000174
	(0.0109)	(0.0166)	(0.0106)	(0.00619)	(0.00632)	(0.00687)	(0.00229)	(0.000204)	(0.00356)
Firm characteristics	-0.00108	0.000692	0.00144	1.05e-05	-0.000107	-0.000671	-0.00336	-0.000638	-0.00125
	(0.00313)	(0.00222)	(0.00359)	(0.00114)	(0.00115)	(0.00199)	(0.00810)	(0.00232)	(0.00371)
Hours of work	0.00786	0.00545	0.00540	0.00544	-0.00611	-0.0154*	-0.0178*	-0.0312*	-0.0315*
	(0.00882)	(0.00714)	(0.00561)	(0.00572)	(0.00582)	(0.00938)	(0.0107)	(0.0176)	(0.0187)
Unionization	-0.000525	0.00132	0.00171	0.00258	0.00358	0.00422	0.00484	0.00585	0.00385
	(0.00206)	(0.00405)	(0.00509)	(0.00762)	(0.0105)	(0.0124)	(0.0142)	(0.0172)	(0.0114)
Selectivity bias term	-0.0166	-0.0190	-0.0138	-0.0228	-0.0374**	-0.0220	-0.000764	0.00932	0.0419
	(0.0263)	(0.0221)	(0.0165)	(0.0172)	(0.0178)	(0.0178)	(0.0193)	(0.0258)	(0.0332)
Pure wage structural effect									
Potential experience	-0.148	0.00993	0.0338	-0.00307	0.00372	-0.126	-0.131	0.113	-0.146
	(0.178)	(0.111)	(0.0952)	(0.0859)	(0.0858)	(0.0872)	(0.0999)	(0.158)	(0.245)
Education	-0.531	-1.169***	-0.866***	-0.654***	-0.249	-0.292*	-0.306	-0.550*	-0.615
	(0.350)	(0.213)	(0.183)	(0.164)	(0.162)	(0.165)	(0.190)	(0.302)	(0.477)
Industrial effects	0.516	0.217	0.200	-0.0630	-0.210	0.344**	0.322*	0.230	0.267
	(0.344)	(0.210)	(0.181)	(0.163)	(0.162)	(0.164)	(0.189)	(0.300)	(0.471)
Occupational effects	-0.311	-0.351**	-0.0852	-0.105	0.191	0.113	0.0643	-0.0244	0.681*
	(0.277)	(0.161)	(0.139)	(0.124)	(0.122)	(0.124)	(0.144)	(0.231)	(0.375)
Marital effects	-0.620**	-0.812***	-0.477***	-0.633***	-0.484***	-0.377***	-0.367**	-0.229	0.0576
	(0.268)	(0.169)	(0.144)	(0.131)	(0.130)	(0.131)	(0.150)	(0.237)	(0.368)
Religion	-0.483	0.0236	0.0889	0.121	0.0888	-0.0825	-0.0593	0.213	-0.159
	(0.561)	(0.302)	(0.263)	(0.230)	(0.225)	(0.229)	(0.269)	(0.439)	(0.741)
Regional effects	-0.733	-0.497	-0.420	-0.326	-0.371	-0.271	-0.411	-0.710	-1.837**
	(0.664)	(0.399)	(0.343)	(0.307)	(0.305)	(0.310)	(0.358)	(0.570)	(0.904)
Firm characteristics	0.0181	-0.341	0.270	-0.0408	-0.120	0.0674	0.00436	-1.189**	-1.462*
	(0.595)	(0.346)	(0.299)	(0.266)	(0.263)	(0.267)	(0.310)	(0.497)	(0.803)
Hours of work	-0.557	-0.131	0.00661	0.171	0.201	-0.128	0.361	-0.0625	-0.979
	(0.471)	(0.282)	(0.243)	(0.218)	(0.216)	(0.219)	(0.253)	(0.404)	(0.641)
Unionization	-0.0683*	-0.00992	0.00159	0.00669	0.0339*	0.0534***	0.0369*	0.0212	-0.0431
	(0.0405)	(0.0217)	(0.0187)	(0.0166)	(0.0178)	(0.0199)	(0.0208)	(0.0315)	(0.0517)
Selectivity bias term	0.0617	-0.713**	-0.568**	-0.724***	-0.465**	-0.254	-0.487*	-0.709*	-0.756
	(0.468)	(0.297)	(0.255)	(0.231)	(0.231)	(0.234)	(0.267)	(0.422)	(0.649)
Intercept	3.233*	3.814***	1.917**	2.332**	1.432*	1.00742	1.0491	2.875*	4.741**
	(1.351)	(0.816)	(0.702)	(0.629)	(0.626)	(0.635)	(0.732)	(0 1.166)	(1.844)
No. of observations	747	747	747	747	747	747	747	747	747
Informal Sector									
Pure composition effect									
Potential experience	0.00377	-0.000585	0.00387	0.00186	0.000217	0.00117	0.00332	0.00593**	-1.15e-05
	(0.00624)	(0.00668)	(0.00303)	(0.00216)	(0.00189)	(0.00194)	(0.00222)	(0.00267)	(0.00231)
Education	0.0324***	0.0269***	0.0169***	0.0124***	0.0129***	0.0185***	0.0207***	0.0195***	0.0181***
	(0.00991)	(0.00994)	(0.00479)	(0.00354)	(0.00339)	(0.00419)	(0.00459)	(0.00448)	(0.00446)
Industrial effects	0.00431	0.00603	0.00395	0.00240	0.00230	0.00383	0.00483	0.00294	0.00188
	(0.00406)	(0.00537)	(0.00332)	(0.00206)	(0.00196)	(0.00315)	(0.00395)	(0.00248)	(0.00171)
Occupational effects	0.00111	-0.00164	-0.000147	0.000258	0.000943	0.00117	0.000990	0.000658	0.000923
	(0.00229)	(0.00330)	(0.000468)	(0.000571)	(0.00185)	(0.00228)	(0.00194)	(0.00131)	(0.00182)
Marital effects	0.00306	0.000850	-6.66e-05	0.00162	0.00367	0.00502	0.00510	0.00623	0.00906*
	(0.00367)	(0.00351)	(0.00147)	(0.00145)	(0.00238)	(0.00313)	(0.00319)	(0.00384)	(0.00548)
Religion	0.00426	0.00191	-0.000242	0.000301	8.59e-05	0.000451	0.000892	0.000726	0.000778
	(0.00452)	(0.00254)	(0.000758)	(0.000611)	(0.000486)	(0.000661)	(0.00103)	(0.000897)	(0.000972)
Regional effects	0.0166*	0.0256*	0.0153**	0.0143**	0.0146**	0.0112**	0.0109**	0.0108**	0.00819*
	(0.00885)	(0.0131)	(0.00769)	(0.00714)	(0.00724)	(0.00560)	(0.00547)	(0.00544)	(0.00422)
Firm characteristics	0.00940	0.0104	0.00559	0.00451	0.00483	0.00478	0.00403	0.00298	0.00138
	(0.00975)	(0.0108)	(0.00576)	(0.00465)	(0.00497)	(0.00492)	(0.00416)	(0.00309)	(0.00153)
Hours of work	0.00576	0.0158	0.00829	0.00647	0.00460	0.00250	0.000998	0.00102	-1.01e-05
	(0.00578)	(0.0153)	(0.00797)	(0.00622)	(0.00443)	(0.00245)	(0.00111)	(0.00114)	(0.000649)
Unionization	-0.00203	-0.00124	-0.000238	0.000223	0.000473	0.00162	0.000783	0.00146	0.00224
	(0.00273)	(0.00202)	(0.000649)	(0.000508)	(0.000685)	(0.00197)	(0.00102)	(0.00180)	(0.00272)

Selectivity bias term	-0.00737	-0.0154*	-0.00118	0.00153	0.00109	-1.86e-05	-2.56e-05	-0.00266	-0.0133***
	(0.00675)	(0.00809)	(0.00300)	(0.00224)	(0.00201)	(0.00201)	(0.00213)	(0.00231)	(0.00422)
Pure wage structural effect									
Potential experience	-0.117	-0.373**	-0.121*	0.000434	-0.0262	-0.0236	-0.0502	0.0428	-0.0861
	(0.117)	(0.160)	(0.0668)	(0.0410)	(0.0378)	(0.0377)	(0.0418)	(0.0472)	(0.0550)
Education	0.0236	-0.360	-0.0852	0.0240	0.0135	0.0160	-0.0170	-0.0382	-0.129
	(0.180)	(0.246)	(0.104)	(0.0631)	(0.0582)	(0.0581)	(0.0647)	(0.0734)	(0.0857)
Industrial effects	-0.279*	-0.420**	-0.134	-0.0761	-0.0279	0.114**	0.217***	0.138**	0.122*
	(0.151)	(0.207)	(0.0857)	(0.0528)	(0.0487)	(0.0485)	(0.0538)	(0.0606)	(0.0703)
Occupational effects	-0.161	-1.637***	-0.564***	-0.279**	-0.187	0.160	0.0432	-0.0853	0.0596
	(0.360)	(0.486)	(0.212)	(0.127)	(0.117)	(0.117)	(0.132)	(0.151)	(0.179)
Marital effects	-0.294	-0.400	-0.208**	-0.119*	-0.225***	-0.190***	-0.221***	-0.259***	-0.215**
	(0.180)	(0.246)	(0.103)	(0.0629)	(0.0580)	(0.0579)	(0.0643)	(0.0727)	(0.0846)
Religion	0.262	0.460	0.260*	0.0909	0.0758	0.126	0.0102	-0.0525	-0.0143
	(0.250)	(0.338)	(0.149)	(0.0885)	(0.0816)	(0.0820)	(0.0928)	(0.106)	(0.126)
Regional effects	-0.335	0.514	0.185	0.0774	0.0884	-0.120	-0.363***	-0.307**	-0.309**
	(0.295)	(0.402)	(0.170)	(0.103)	(0.0953)	(0.0952)	(0.106)	(0.120)	(0.141)
Firm characteristics	0.293*	0.598**	0.195**	0.0747	0.0845	0.0265	-0.113*	-0.306***	-0.269***
	(0.171)	(0.233)	(0.0979)	(0.0597)	(0.0551)	(0.0550)	(0.0612)	(0.0695)	(0.0811)
Hours of work	0.490**	0.401	0.0690	0.0983	-0.0431	-0.140*	-0.204**	-0.188*	-0.190*
	(0.237)	(0.324)	(0.136)	(0.0831)	(0.0766)	(0.0765)	(0.0852)	(0.0966)	(0.113)
Unionization	-0.00505	0.00185	0.000148	-0.00125	-0.00115	-0.000366	-0.00460	0.00236	0.00466
	(0.00808)	(0.0108)	(0.00473)	(0.00284)	(0.00262)	(0.00261)	(0.00315)	(0.00343)	(0.00415)
Selectivity bias term	-0.617	-1.040*	-0.190	0.146	0.173	0.275**	0.137	-0.197	-0.236
	(0.428)	(0.587)	(0.242)	(0.149)	(0.138)	(0.137)	(0.152)	(0.171)	(0.198)
Intercept	0.887	2.421**	0.691	0.111	0.236	-0.0910	0.815***	1.560***	1.497***
	(0.850)	(1.160)	(0.488)	(0.298)	(0.274)	(0.274)	(0.305)	(0.346)	(0.403)
No. of observations	4,677	4,677	4,677	4,677	4,677	4,677	4,677	4,677	4,677

Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: The dependent variable is the estimated RIF at the respective decile of the log earnings. The gender wage gap is the difference between log male earnings and log female earnings. Sampling weights are used in the estimations. Standard errors reported in parentheses are robust. The reweighting factors are estimated using the logit model. *** p<0.01, ** p<0.05, * p<0.1.

Appendix III.

Table A3: Wage decomposition results: Percentile ratios, Gini coefficient, and variance by age cohorts

Age 35+	(1)	(2)	(3)	(4)	(5)
	Iqr9010	Iqr5010	Iqr9050	Gini	Var
Log Male earnings (M)	3.893***	2.300***	1.593***	0.0908***	2.361***
	(0.138)	(0.128)	(0.0472)	(0.00196)	(0.0879)
Log Female earnings (F)	3.859***	2.028***	1.831***	0.0992***	2.691***
	(0.183)	(0.170)	(0.0671)	(0.00268)	(0.129)
Gender Pay Gap	0.0340	0.272	-0.238***	-0.00838**	-0.330**
	(0.229)	(0.213)	(0.0820)	(0.00332)	(0.156)
Reweighting decomposition					
Counterfactual (C)	3.851***	2.330***	1.520***	0.0925***	2.533***
	(0.142)	(0.133)	(0.0466)	(0.00196)	(0.0939)
Total composition effect (M – C)	0.0420	-0.0307	0.0727	-0.00168	-0.172
	(0.198)	(0.185)	(0.0663)	(0.00278)	(0.129)
Total structural effect (C – F)	-0.00794	0.302	-0.310***	-0.00669**	-0.158
	(0.232)	(0.216)	(0.0816)	(0.00332)	(0.160)
RIF aggregate decomposition					
Pure composition effect	-0.0537	0.0659	-0.120***	-0.00180*	-0.156***
	(0.0639)	(0.0539)	(0.0282)	(0.00105)	(0.0450)
Specification error	0.0957	-0.0967	0.192***	0.000121	-0.0160
	(0.197)	(0.185)	(0.0658)	(0.00270)	(0.126)
Pure structural effect	0.506*	0.580**	-0.0733	0.00473	0.314*
	(0.268)	(0.254)	(0.0926)	(0.00374)	(0.182)
Reweighting error	-0.514***	-0.277*	-0.237***	-0.0114***	-0.472***
	(0.154)	(0.143)	(0.0503)	(0.00218)	(0.102)
Age 15-34 years					
Log Male earnings (M)	3.676***	2.480***	1.197***	0.0810***	1.851***

	(0.160)	(0.154)	(0.0363)	(0.00188)	(0.0728)
Log Female earnings (F)	3.611***	2.264***	1.346***	0.0869***	2.097***
	(0.237)	(0.226)	(0.0595)	(0.00265)	(0.115)
Gender Pay Gap	0.0657	0.215	-0.149**	-0.00589*	-0.245*
	(0.286)	(0.273)	(0.0697)	(0.00325)	(0.136)
Reweighting decomposition					
Counterfactual (C)	3.816***	2.626***	1.190***	0.0846***	2.016***
	(0.109)	(0.101)	(0.0370)	(0.00194)	(0.0781)
Total composition effect (M – C)	-0.139	-0.147	0.00734	-0.00358	-0.165
	(0.194)	(0.184)	(0.0518)	(0.00270)	(0.107)
Total structural effect (C – F)	0.205	0.362	-0.157**	-0.00231	-0.0805
	(0.260)	(0.248)	(0.0701)	(0.00329)	(0.139)
RIF aggregate decomposition					
Pure composition effect	-0.0415	0.0390	-0.0804***	-0.000804	-0.0367
	(0.0761)	(0.0716)	(0.0199)	(0.00101)	(0.0347)
Specification error	-0.0979	-0.186	0.0878*	-0.00278	-0.128
	(0.200)	(0.191)	(0.0514)	(0.00269)	(0.108)
Pure structural effect	0.0505	0.167	-0.116	-0.00526	-0.157
	(0.272)	(0.260)	(0.0734)	(0.00355)	(0.151)
Reweighting error	0.155	0.195**	-0.0405	0.00295	0.0768
	(0.102)	(0.0929)	(0.0365)	(0.00189)	(0.0741)

Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Sampling weights are used in the estimations. Standard errors reported in parentheses are robust. The reweighting factors are estimated using the logit model. *** p<0.01, ** p<0.05, * p<0.1. The iqr9010 is the difference between the 90th percentile and the 10th percentile of log male-female earnings. The series iqr5010 and iqr9050 are computed analogously. The Gini coefficient is expressed in percentage points and ranges from 0 (perfect equality) to 100 (perfect inequality). Variance captures the effect of covariates on the variance of the distributions of log earnings.

Appendix IV.

Table A4: Wage decomposition results: Percentile ratios, Gini coefficient, and variance by sectors of employment

Public sector	(1)	(2)	(3)	(4)	(5)
	Iqr9010	Iqr5010	Iqr9050	Gini	Var
Log Male earnings (M)	2.368***	1.411***	0.956***	0.0543***	1.107***
	(0.0784)	(0.0654)	(0.0578)	(0.00219)	(0.133)
Log Female earnings (F)	2.391***	1.324***	1.067***	0.0556***	1.066***
	(0.0942)	(0.0775)	(0.0658)	(0.00208)	(0.0844)
Gender Pay Gap	-0.0230	0.0877	-0.111	-0.00129	0.0406
	(0.123)	(0.101)	(0.0876)	(0.00302)	(0.158)
Reweighting decomposition					
Counterfactual (C)	2.264***	1.368***	0.896***	0.0508***	0.981***
	(0.0789)	(0.0635)	(0.0557)	(0.00201)	(0.115)
Total composition effect (M – C)	0.104	0.0436	0.0607	0.00346	0.126
	(0.111)	(0.0912)	(0.0803)	(0.00297)	(0.176)
Total structural effect (C – F)	-0.127	0.0441	-0.171**	-0.00475	-0.0854
	(0.123)	(0.100)	(0.0863)	(0.00289)	(0.143)
RIF aggregate decomposition					
Pure composition effect	0.0507	0.0196	0.0312	0.00255**	0.0743
	(0.0436)	(0.0372)	(0.0333)	(0.00124)	(0.0708)
Specification error	0.0536	0.0241	0.0295	0.000912	0.0518
	(0.117)	(0.0960)	(0.0841)	(0.00312)	(0.188)
Pure structural effect	-0.160	0.0204	-0.181**	-0.00542*	-0.0977
	(0.131)	(0.105)	(0.0898)	(0.00310)	(0.158)
Reweighting error	0.0329	0.0237	0.00923	0.000661	0.0122
	(0.0511)	(0.0410)	(0.0381)	(0.00136)	(0.0716)
Private formal sector					
Log Male earnings (M)	2.048***	0.946***	1.102***	0.0553***	1.132***
	(0.101)	(0.0618)	(0.0850)	(0.00291)	(0.121)
Log Female earnings (F)	2.645***	1.183***	1.463***	0.0628***	1.522***
	(0.207)	(0.117)	(0.170)	(0.00458)	(0.277)
Gender Pay Gap	-0.598***	-0.237*	-0.361*	-0.00752	-0.390
	(0.230)	(0.132)	(0.190)	(0.00543)	(0.302)
Reweighting decomposition					
Counterfactual (C)	2.145***	0.930***	1.215***	0.0576***	1.207***

	(0.104)	(0.0571)	(0.0937)	(0.00284)	(0.122)
Total composition effect (M – C)	-0.0974	0.0153	-0.113	-0.00233	-0.0744
	(0.145)	(0.0842)	(0.127)	(0.00406)	(0.172)
Total structural effect (C – F)	-0.500**	-0.252*	-0.248	-0.00519	-0.316
	(0.231)	(0.130)	(0.194)	(0.00539)	(0.302)
RIF aggregate decomposition					
Pure composition effect	-0.231***	-0.0231	-0.207***	-0.00617***	-0.256***
	(0.0860)	(0.0438)	(0.0704)	(0.00222)	(0.0890)
Specification error	0.133	0.0384	0.0948	0.00385	0.182
	(0.143)	(0.0882)	(0.126)	(0.00418)	(0.179)
Pure structural effect	-0.631***	-0.330**	-0.301	-0.00497	-0.258
	(0.233)	(0.137)	(0.200)	(0.00576)	(0.315)
Reweighting error	0.131	0.0782	0.0528	-0.000216	-0.0574
	(0.109)	(0.0580)	(0.0954)	(0.00279)	(0.117)
Private informal sector					
Log Male earnings (M)	3.626***	2.597***	1.029***	0.0846***	1.854***
	(0.0632)	(0.0581)	(0.0256)	(0.00156)	(0.0543)
Log Female earnings (F)	3.722***	2.651***	1.071***	0.0863***	1.803***
	(0.0754)	(0.0661)	(0.0374)	(0.00230)	(0.0771)
Gender wage gap	-0.0957	-0.0535	-0.0422	-0.00169	0.0505
	(0.0984)	(0.0880)	(0.0453)	(0.00278)	(0.0943)
Reweighting decomposition					
Counterfactual (C)	3.752***	2.709***	1.042***	0.0870***	1.916***
	(0.0629)	(0.0570)	(0.0263)	(0.00158)	(0.0543)
Total composition effect (M – C)	-0.125	-0.112	-0.0136	-0.00238	-0.0621
	(0.0892)	(0.0814)	(0.0367)	(0.00222)	(0.0768)
Total structural effect (C – F)	0.0298	0.0584	-0.0286	0.000689	0.113
	(0.0982)	(0.0873)	(0.0457)	(0.00279)	(0.0943)
RIF aggregate decomposition					
Pure composition effect	-0.0420**	-0.0256*	-0.0164*	-0.00122*	-0.0220
	(0.0186)	(0.0143)	(0.00929)	(0.000642)	(0.0179)
Specification error	-0.0835	-0.0863	0.00284	-0.00116	-0.0401
	(0.0889)	(0.0817)	(0.0362)	(0.00216)	(0.0760)
Pure structural effect	0.0883	0.0148	0.0735	0.00380	0.170
	(0.119)	(0.107)	(0.0533)	(0.00317)	(0.110)
Reweighting error	-0.0585	0.0436	-0.102***	-0.00311*	-0.0576
	(0.0694)	(0.0624)	(0.0294)	(0.00181)	(0.0608)

Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Sampling weights are used in the estimations. Standard errors reported in parentheses are robust. The reweighting factors are estimated using the logit model. *** p<0.01, ** p<0.05, * p<0.1. The iqr9010 is the difference between the 90th percentile and the 10th percentile of log male-female earnings. The series iqr5010 and iqr9050 are computed analogously. The Gini coefficient is expressed in percentage points and ranges from 0 (perfect equality) to 100 (perfect inequality). Variance captures the effect of covariates on the variance of the distributions of log earnings.

Appendix V.

Table A5: Decomposing gender wage gap by percentiles: The RIF-Oaxaca detailed decomposition (Full-sample).

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Mean	10%	20%	30%	40%	50%	60%	70%	80%	90%
Log Male earnings (M)	8.860***	6.504***	8.098***	8.553***	8.856***	9.045***	9.337***	9.700***	9.983***	10.62***
	(0.0232)	(0.0583)	(0.0420)	(0.0244)	(0.0207)	(0.0206)	(0.0217)	(0.0235)	(0.0277)	(0.0329)
Log Female earnings (F)	8.746***	6.436***	8.025***	8.399***	8.625***	8.767***	9.133***	9.512***	10.01***	10.65***
	(0.0313)	(0.174)	(0.0376)	(0.0273)	(0.0246)	(0.0266)	(0.0345)	(0.0405)	(0.0486)	(0.0404)
Gender Pay gap	0.114***	0.0678	0.0728	0.154***	0.231***	0.279***	0.204***	0.187***	-0.0306	-0.0210
	(0.0390)	(0.183)	(0.0564)	(0.0366)	(0.0321)	(0.0336)	(0.0408)	(0.0468)	(0.0560)	(0.0520)
Reweighting decomposition										
Counterfactual	8.584***	6.129***	7.721***	8.219***	8.508***	8.771***	8.979***	9.313***	9.753***	10.48***
	(0.0313)	(0.0974)	(0.0562)	(0.0304)	(0.0247)	(0.0254)	(0.0306)	(0.0373)	(0.0420)	(0.0456)
Total composition effect	-0.162***	-0.307	-0.304***	-0.180***	-0.117***	0.00456	-0.154***	-0.199***	-0.261***	-0.168***
	(0.0443)	(0.199)	(0.0677)	(0.0409)	(0.0348)	(0.0368)	(0.0461)	(0.0551)	(0.0642)	(0.0609)
Total structural effect	0.277***	0.375***	0.377***	0.334***	0.347***	0.274***	0.358***	0.387***	0.230***	0.147***
	(0.0389)	(0.113)	(0.0702)	(0.0390)	(0.0322)	(0.0327)	(0.0375)	(0.0441)	(0.0503)	(0.0562)

RIF aggregate decomposition										
Pure composition effect	-0.158***	-0.513***	-0.160***	-0.121***	-0.109***	-0.100***	-0.134***	-0.169***	-0.212***	-0.127***
	(0.0302)	(0.0984)	(0.0259)	(0.0202)	(0.0195)	(0.0233)	(0.0329)	(0.0405)	(0.0480)	(0.0343)
Specification error	-0.00477	0.206	-0.144**	-0.0583	-0.00748	0.105***	-0.0199	-0.0304	-0.0484	-0.0410
	(0.0350)	(0.202)	(0.0639)	(0.0376)	(0.0311)	(0.0317)	(0.0371)	(0.0420)	(0.0488)	(0.0514)
Pure wage structural effect	0.270***	0.351***	0.346***	0.342***	0.360***	0.297***	0.378***	0.351***	0.302***	0.149***
	(0.0371)	(0.134)	(0.0787)	(0.0420)	(0.0334)	(0.0333)	(0.0365)	(0.0415)	(0.0454)	(0.0537)
Reweighting error	0.00714	0.0243	0.0307	-0.00787	-0.0130	-0.0231	-0.0206	0.0356	-0.0718*	-0.00213
	(0.0312)	(0.0835)	(0.0498)	(0.0277)	(0.0231)	(0.0241)	(0.0303)	(0.0380)	(0.0433)	(0.0452)
Pure composition effect										
Educational effects	-0.0383**	-0.0994***	-0.0196***	-0.0156***	-0.0177***	-0.0273***	-0.0371***	-0.0401***	-0.0460***	-0.0473***
	(0.0121)	(0.0369)	(0.00739)	(0.00565)	(0.00602)	(0.00877)	(0.0118)	(0.0128)	(0.0147)	(0.0150)
Potential experience	0.00300	0.0282	0.00514	0.00361	0.000472	0.00124	3.25e-05	-0.00178	-0.00202	-0.00148
	(0.00476)	(0.0179)	(0.00338)	(0.00242)	(0.00145)	(0.00270)	(0.00408)	(0.00759)	(0.0120)	(0.00914)
Married	-0.00962	-0.108*	-0.0224*	-0.0135	-0.0100	-0.00114	0.00213	0.0236**	0.0306**	0.00219
	(0.00795)	(0.0571)	(0.0118)	(0.00825)	(0.00716)	(0.00721)	(0.00875)	(0.0101)	(0.0123)	(0.0111)
Industrial effects	-0.0131**	-0.0782**	-0.0265**	-0.0177**	-0.0123**	-0.00160	0.00359	0.00228	-0.00377	-0.00179
	(0.00518)	(0.0320)	(0.01000)	(0.00673)	(0.00483)	(0.00208)	(0.00274)	(0.00282)	(0.00353)	(0.00315)
Occupational effects	0.0114**	0.0502*	0.0107**	0.00549	0.00565*	0.00472	0.0121**	0.0117**	0.00430	0.00770
	(0.00443)	(0.0259)	(0.00539)	(0.00352)	(0.00318)	(0.00311)	(0.00482)	(0.00502)	(0.00476)	(0.00486)
Sectoral effects	-0.0620**	-0.130***	-0.0463**	-0.0368**	-0.0404**	-0.0544**	-0.0869**	-0.102***	-0.0943**	-0.0466**
	(0.0153)	(0.0438)	(0.0127)	(0.00979)	(0.0103)	(0.0134)	(0.0211)	(0.0248)	(0.0232)	(0.0126)
Regional effects	-0.00890	-0.0198	-0.00521	-0.00639	-0.00724	-0.00891	-0.0116	-0.0108	-0.00811	-0.00555
	(0.00620)	(0.0156)	(0.00391)	(0.00452)	(0.00507)	(0.00619)	(0.00804)	(0.00754)	(0.00580)	(0.00410)
Unionization	-0.00913*	0.00314	0.000964	-0.000409	-0.00197	-0.00436*	-0.00796*	-0.0134**	-0.0290**	-0.0265**
	(0.00413)	(0.0129)	(0.00268)	(0.00188)	(0.00182)	(0.00243)	(0.00381)	(0.00589)	(0.0121)	(0.0111)
Selectivity bias term	-0.0309**	-0.158*	-0.0571**	-0.0400**	-0.0257**	-0.00835	-0.00840	-0.0380**	-0.0637**	-0.00726
	(0.0127)	(0.0894)	(0.0188)	(0.0132)	(0.0114)	(0.0115)	(0.0139)	(0.0157)	(0.0193)	(0.0177)
Pure wage structural effect										
Educational effects	-0.130**	-0.434**	-0.340***	-0.0742	0.0127	0.0269	-0.0407	-0.0942	-0.00577	0.0375
	(0.0623)	(0.220)	(0.132)	(0.0708)	(0.0564)	(0.0560)	(0.0609)	(0.0684)	(0.0754)	(0.0894)
Potential experience	-0.0918	-0.104	-0.208	-0.0449	0.0200	0.0440	-0.0193	-0.0456	-0.177**	-0.0270
	(0.0735)	(0.256)	(0.155)	(0.0837)	(0.0669)	(0.0662)	(0.0716)	(0.0801)	(0.0883)	(0.105)
Married	0.256***	0.696***	0.392***	0.243***	0.252***	0.260***	0.250***	0.190***	0.0744	-0.0483
	(0.0642)	(0.223)	(0.135)	(0.0731)	(0.0585)	(0.0579)	(0.0625)	(0.0697)	(0.0768)	(0.0913)
Industrial effects	0.0335	-0.371**	-0.188*	0.0189	0.0219	0.132***	0.188***	0.190***	0.103*	0.0885
	(0.0521)	(0.181)	(0.110)	(0.0594)	(0.0475)	(0.0470)	(0.0507)	(0.0566)	(0.0624)	(0.0741)
Occupational effects	-0.304**	-0.317	-0.896***	-0.239*	0.000301	0.187*	0.167	-0.244*	0.0701	-0.532***
	(0.121)	(0.441)	(0.257)	(0.137)	(0.108)	(0.108)	(0.119)	(0.136)	(0.149)	(0.176)
Sectoral effects	0.219	0.351	0.288	0.0340	-0.0407	0.0735	0.502***	1.049***	0.430**	-0.250
	(0.151)	(0.530)	(0.319)	(0.172)	(0.137)	(0.136)	(0.147)	(0.165)	(0.182)	(0.216)
Regional effects	-0.164*	-0.480	-0.0482	0.0223	0.00584	-0.141	-0.308***	-0.396***	-0.414***	-0.158
	(0.0982)	(0.347)	(0.208)	(0.112)	(0.0890)	(0.0883)	(0.0960)	(0.108)	(0.119)	(0.141)
Unionization	0.258	0.483	-0.199	0.00569	0.00470	0.00840	-0.00263	-0.00871	-0.0138	-0.0634**
	(0.254)	(0.897)	(0.538)	(0.0114)	(0.00909)	(0.00903)	(0.00979)	(0.0110)	(0.0121)	(0.0148)
Selectivity bias term	-0.00515	-0.520	0.190	0.607**	0.511**	0.0953	-0.259	-0.212	-0.223	-0.112
	(0.244)	(0.860)	(0.516)	(0.277)	(0.221)	(0.219)	(0.238)	(0.267)	(0.295)	(0.350)
Intercept	0.198	1.048	1.354*	-0.232	-0.428	-0.388	-0.0991	-0.0771	0.458	1.213***
	(0.377)	(1.332)	(0.797)	(0.355)	(0.283)	(0.281)	(0.306)	(0.344)	(0.378)	(0.449)
No. of observations	6,653	6,653	6,653	6,653	6,653	6,653	6,653	6,653	6,653	6,653

Source: Author's calculations (2024) based on Kenya continuous Household Survey-2021 data. Note: Unweighted data. Note: The dependent variable is the estimated RIF at the respective decile of the log earnings. The gender wage gap is the difference between log male earnings and log female earnings. Sampling weights are not used in the estimations. Standard errors reported in parentheses are robust. The reweighting factors were estimated using the logit model. *** p<0.01, ** p<0.05, * p<0.1.

Appendix VI.

Table A6: Gender pay gap for Low-educated workers across age cohorts and employment sectors

	15-34 years			**35+**			**Formal sector**			**Informal sector**		
	Observed gap	Composition effect	Wage structural effect	Observed gap	Composition effect	Wage structural effect	Observed gap	Composition effect	Wage structural effect	Observed gap	Composition effect	Wage structural effect
0.1	0.430***	0.125	0.305**	0.387*	-0.0936	0.481**	0.369**	-0.0296	0.399***	0.370***	0.110	0.260***
	(0.151)	(0.113)	(0.151)	(0.223)	(0.166)	(0.205)	(0.144)	(0.0930)	(0.144)	(0.0949)	(0.0882)	(0.0934)
0.2	0.403***	0.153*	0.250*	0.382***	0.0660	0.316**	0.170	0.0508	0.119	0.230	-0.0436	0.273*
	(0.141)	(0.0905)	(0.143)	(0.127)	(0.105)	(0.127)	(0.106)	(0.0700)	(0.106)	(0.140)	(0.119)	(0.142)
0.3	0.313***	0.103**	0.209***	0.502***	0.0461	0.456***	0.136	0.0264	0.110	0.267***	0.0454	0.222***
	(0.0613)	(0.0526)	(0.0628)	(0.0641)	(0.0541)	(0.0640)	(0.0840)	(0.0616)	(0.0841)	(0.0564)	(0.0480)	(0.0558)
0.4	0.225***	0.0177	0.207***	0.457***	0.0856*	0.371***	0.231***	0.0107	0.220***	0.317***	0.155***	0.162***
	(0.0460)	(0.0423)	(0.0466)	(0.0506)	(0.0443)	(0.0509)	(0.0736)	(0.0530)	(0.0731)	(0.0378)	(0.0342)	(0.0397)
0.5	0.293***	0.0654*	0.228***	0.532***	-0.00375	0.536***	0.0308	-0.138***	0.169**	0.357***	0.0356	0.322***
	(0.0439)	(0.0385)	(0.0442)	(0.0502)	(0.0430)	(0.0497)	(0.0673)	(0.0533)	(0.0664)	(0.0332)	(0.0299)	(0.0331)
0.6	0.355***	0.0825**	0.273***	0.515***	0.00712	0.508***	0.204***	0.0433	0.161**	0.355***	0.117***	0.238***
	(0.0454)	(0.0377)	(0.0454)	(0.0526)	(0.0434)	(0.0522)	(0.0684)	(0.0568)	(0.0674)	(0.0329)	(0.0290)	(0.0326)
0.7	0.345***	0.0581	0.287***	0.555***	0.0700	0.485***	0.290***	0.0455	0.245***	0.396***	-0.0124	0.408***
	(0.0493)	(0.0381)	(0.0495)	(0.0579)	(0.0430)	(0.0577)	(0.0724)	(0.0635)	(0.0721)	(0.0347)	(0.0297)	(0.0347)
0.8	0.301***	0.0617	0.239***	0.393***	0.0971**	0.296***	0.236**	0.0142	0.222**	0.425***	0.0686**	0.356***
	(0.0493)	(0.0389)	(0.0496)	(0.0657)	(0.0418)	(0.0651)	(0.0933)	(0.0694)	(0.0931)	(0.0404)	(0.0313)	(0.0403)
0.9	0.294***	0.0553	0.238***	0.315***	0.116**	0.200**	0.141	0.0524	0.0890	0.301***	0.0353	0.266***
	(0.0485)	(0.0426)	(0.0489)	(0.0806)	(0.0541)	(0.0787)	(0.0946)	(0.0688)	(0.0937)	(0.0463)	(0.0343)	(0.0464)

Source: Author's calculations (2025) based on KCHS-2021 data. Note: weighted data. Note: *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Gender pay gap for Highly educated workers across age cohorts and employment sectors

	15-34 years			**35+**			**Formal sector**			**Informal sector**		
	Observed gap	Composition effect	Wage structural effect	Observed gap	Composition effect	Wage structural effect	Observed gap	Composition effect	Wage structural effect	Observed gap	Composition effect	Wage structural effect
0.1	0.152	0.116	0.0367	0.265**	-0.0172	0.282**	0.405***	0.0678	0.338***	-0.150	0.658	-0.808
	(0.134)	(0.177)	(0.162)	(0.128)	(0.115)	(0.127)	(0.0930)	(0.0821)	(0.0921)	(0.652)	(0.784)	(0.579)
0.2	0.233**	0.221**	0.0119	0.101	-0.0159	0.116	0.356***	0.249***	0.106	0.228	0.129	0.0984
	(0.0998)	(0.105)	(0.104)	(0.0963)	(0.0990)	(0.0916)	(0.0729)	(0.0749)	(0.0761)	(0.170)	(0.167)	(0.171)
0.3	0.196**	0.118	0.0782	0.236***	-0.0194	0.256***	0.388***	0.155**	0.233***	0.285**	0.190	0.0953
	(0.0884)	(0.0870)	(0.0892)	(0.0838)	(0.0800)	(0.0815)	(0.0692)	(0.0680)	(0.0679)	(0.141)	(0.142)	(0.143)
0.4	0.183**	0.0966	0.0867	0.218***	0.0316	0.187**	0.285***	0.0957	0.189***	0.472***	0.193	0.279**
	(0.0834)	(0.0819)	(0.0836)	(0.0816)	(0.0774)	(0.0796)	(0.0688)	(0.0683)	(0.0669)	(0.138)	(0.130)	(0.138)
0.5	0.205**	0.0845	0.121	0.308***	0.0849	0.223***	0.328***	0.110*	0.218***	0.500***	0.105	0.394***
	(0.0834)	(0.0810)	(0.0834)	(0.0805)	(0.0763)	(0.0787)	(0.0684)	(0.0669)	(0.0688)	(0.133)	(0.119)	(0.131)
0.6	0.213**	0.194**	0.0183	0.223***	0.0673	0.155*	0.338***	0.127**	0.211***	0.419***	0.0347	0.384***
	(0.0852)	(0.0823)	(0.0854)	(0.0821)	(0.0790)	(0.0804)	(0.0678)	(0.0643)	(0.0690)	(0.133)	(0.116)	(0.131)
0.7	0.0933	0.000607	0.0927	0.268***	0.0630	0.205**	0.250***	0.133**	0.117*	0.415***	0.142	0.273**
	(0.0902)	(0.0874)	(0.0947)	(0.0842)	(0.0839)	(0.0829)	(0.0697)	(0.0643)	(0.0701)	(0.138)	(0.114)	(0.135)
0.8	0.130	0.100	0.0300	0.333***	0.0393	0.294***	0.121	0.0854	0.0359	0.464***	0.00678	0.457***
	(0.109)	(0.0965)	(0.115)	(0.0927)	(0.100)	(0.0955)	(0.0768)	(0.0709)	(0.0768)	(0.142)	(0.121)	(0.146)
0.9	-0.0506	0.0205	-0.0712	0.477***	0.0523	0.425***	0.279***	0.109	0.170	0.613***	0.107	0.505***
	(0.138)	(0.102)	(0.145)	(0.124)	(0.152)	(0.134)	(0.105)	(0.116)	(0.109)	(0.137)	(0.118)	(0.137)

Source: Author's calculations (2025) based on KCHS-2021 data. Note: weighted data. Note: *** p<0.01, ** p<0.05, * p<0.1.

Appendix VII.

Table A8: OLS and Heckman Selectivity corrected Log earnings by gender without human capital elements (*F*ull sample)

	All		Men		Women	
	OLS	Heckman	OLS	Heckman	OLS	Heckman
Female	-0.160***	-0.201***	-	-	-	-
	(0.0353)	(0.0357)				
Married	0.0789**	0.219***	0.212***	0.365***	-0.0852*	0.0207
	(0.0322)	(0.0375)	(0.0429)	(0.0493)	(0.0496)	(0.0580)
Household size	-0.0360***	-0.0495***	-0.0407***	-0.0543***	-0.0306***	-0.0425***
	(0.00641)	(0.00665)	(0.00807)	(0.00833)	(0.0105)	(0.0111)
Urban	0.248***	0.195***	0.204***	0.143***	0.294***	0.261***
	(0.0345)	(0.0351)	(0.0441)	(0.0450)	(0.0555)	(0.0562)
Christian	0.280***	0.293***	0.322***	0.334***	0.111	0.123
	(0.0677)	(0.0674)	(0.0754)	(0.0751)	(0.164)	(0.164)
Islamic	0.460***	0.487***	0.529***	0.559***	0.280	0.295
	(0.0904)	(0.0902)	(0.103)	(0.103)	(0.203)	(0.203)
Firm size	0.206***	0.208***	0.203***	0.208***	0.189***	0.187***
	(0.0195)	(0.0194)	(0.0247)	(0.0246)	(0.0318)	(0.0318)
Hours of work	0.00796***	0.00786***	0.00662***	0.00655***	0.0105***	0.0104***
	(0.000941)	(0.000938)	(0.00118)	(0.00117)	(0.00161)	(0.00161)
Public sector	0.353***	0.345***	0.332***	0.326***	0.460***	0.449***
	(0.0659)	(0.0656)	(0.0883)	(0.0879)	(0.0980)	(0.0978)
Private informal	-0.662***	-0.627***	-0.633***	-0.589***	-0.674***	-0.655***
	(0.0567)	(0.0567)	(0.0718)	(0.0718)	(0.0938)	(0.0937)
Occ1	0.581***	0.574***	0.587***	0.572***	0.593***	0.595***
	(0.133)	(0.132)	(0.171)	(0.171)	(0.210)	(0.209)
Occ2	0.549***	0.495***	0.779***	0.710***	0.250**	0.215*
	(0.0846)	(0.0846)	(0.116)	(0.116)	(0.126)	(0.126)
Occ3	0.587***	0.562***	0.647***	0.608***	0.432**	0.430**
	(0.0975)	(0.0972)	(0.119)	(0.119)	(0.177)	(0.177)
Occ4	0.421***	0.405***	0.432*	0.435*	0.256	0.243
	(0.146)	(0.146)	(0.255)	(0.253)	(0.184)	(0.184)
Occ5	0.0469	0.0621	0.154	0.165*	-0.141	-0.127
	(0.0688)	(0.0685)	(0.0956)	(0.0952)	(0.0986)	(0.0985)
Occ6	-0.205***	-0.197***	-0.0778	-0.0749	-0.410***	-0.400***
	(0.0607)	(0.0605)	(0.0770)	(0.0766)	(0.1000)	(0.0998)
Occ7	0.0582	0.0724	0.123	0.140	0.00517	0.00895
	(0.0783)	(0.0780)	(0.0926)	(0.0922)	(0.162)	(0.161)
Occ8	-0.0285	-0.0186	0.114	0.119	0.0166	0.0307
	(0.0866)	(0.0863)	(0.101)	(0.101)	(0.227)	(0.226)
Unionization	0.449***	0.435***	0.338***	0.324***	0.597***	0.586***
	(0.0610)	(0.0608)	(0.0811)	(0.0808)	(0.0908)	(0.0907)
Primary sector	-0.390***	-0.396***	-0.315**	-0.326**	-0.529	-0.530
	(0.136)	(0.135)	(0.148)	(0.148)	(0.441)	(0.440)
Manufacturing	-0.0705	-0.0772	-0.0533	-0.0641	-0.161	-0.157
	(0.140)	(0.139)	(0.153)	(0.152)	(0.442)	(0.441)
tertiary_sector1	-0.129	-0.139	-0.0521	-0.0652	-0.379	-0.404
	(0.133)	(0.132)	(0.141)	(0.141)	(0.480)	(0.479)
tertiary_sector2	-0.198	-0.209	-0.117	-0.130	-0.407	-0.415
	(0.138)	(0.138)	(0.158)	(0.157)	(0.438)	(0.437)
tertiary_sector3	-0.135	-0.140	-0.160	-0.162	0.378	0.360
	(0.124)	(0.124)	(0.132)	(0.132)	(0.451)	(0.450)
tertiary_sector4	-0.118	-0.118	-0.0799	-0.0712	-0.261	-0.273
	(0.140)	(0.140)	(0.158)	(0.157)	(0.441)	(0.440)
tertiary_sector5	-0.196	-0.210	-0.173	-0.181	-0.347	-0.362
	(0.135)	(0.134)	(0.154)	(0.154)	(0.434)	(0.433)
tertiary_sector6	-0.113	-0.153	0.0965	0.0467	-0.467	-0.494
	(0.145)	(0.145)	(0.196)	(0.195)	(0.439)	(0.438)
Inverse Mills Ratio		-0.573***		-0.649***		-0.417***
		(0.0792)		(0.105)		(0.120)
Constant	8.400***	8.988***	8.219***	8.876***	8.657***	9.068***
	(0.167)	(0.186)	(0.190)	(0.217)	(0.485)	(0.498)
Observations	6,653	6,653	4,210	4,210	2,443	2,443
R-squared	0.368	0.373	0.328	0.334	0.451	0.454

Source: Author's calculations (2025) based on KCHS-2021 data. Note: weighted data. Note: *** p<0.01, ** p<0.05, * p<0.1.