THE ROLE OF GENDER INEQUALITY IN WAGE GAP: PERSPECTIVE OF SUB-SAHARAN AFRICA AND SOUTH ASIA

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DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the FYP.

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LIST OF ABBREVIATIONS

GD	Gender discrimination
GGGP	Global Gender Gap Report
GII	Gender Inequality Index
GWG	Gender Wage Gap
HDI	Human Development Index
ILO	International Labour Organization
LFPR	Labour Force Participation Rate
SA	South Asia
SDGs	Sustainable Development Goals
SSA	Sub-Saharan Africa
UNDP	United Nations Development Programme
VE	Vulnerable Employment
WG	Wage Gap
WGS	Workplace Gender Discrimination
FEM	Fixed Effect Model
REM	Random Effect Model
BPLM	Breusch-Pagan Lagrange Multiplier Test
Pooled OLS	Pooled Ordinary Least Square

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PERFACE

Gender-based wage disparities remains one of the most persistent and complex issues in achieving global economic equality and social justice. While this issue occurs globally, its expressions and implications vary by place due to differences in socioeconomic systems, cultural norms, and governmental frameworks. The disparity leads to increased poverty rates among women, particularly in single-income homes, and exacerbates economic inequality throughout society. It also impacts families, since reduced household wages can limit children's access to school and healthcare, with long-term consequences for future generations.

Gender inequality significantly contributes to the wage gap by limiting women's equal opportunities, income, and promotion in the workplace. Traditional gender norms and stereotypes frequently position women in low-wage occupations and undervalue the labour that women normally accomplish. Furthermore, women may encounter prejudice in employment, promotions, and wage negotiations, resulting in uneven remuneration even while doing the same job as males. Women earn less on average than men due to institutional inequities, which exacerbates economic disparities and limits women's financial independence. Addressing gender disparity is critical to decreasing the pay gap and ensuring workplace justice.

This research seeks to examine how gender inequality and the gender pay gap affect talent loss, particularly how they interact with one another. The study will look at gender inequality, the gender pay gap, and their interplay to see how they together affect economic development.

ABSTRACT

This study investigates the effects of gender inequality on the wage gap in Sub-Saharan Africa and South Asia. Despite continued attempts to promote gender equality, women in these areas continue to earn less than men due to persisting structural and cultural hurdles. The study uses panel data from 23 countries from 2007 to 2021 using econometric models, Pooled OLS, Fixed Effects, and Random Effects to examine the link between gender inequality and pay differences. The data show a strong and positive association between gender inequality and the pay gap, indicating that increased gender inequality worsens income inequalities between men and women. Gender inequality has a positive and marginally significant link with the gender pay gap, implying that nations with higher gender inequalities have larger wage gaps. The findings suggest policy recommendations for Sub-Saharan Africa and South Asia governments to improve population growth by strengthening labour policies, enhancing access to education and formal employment, and promoting women's leadership to narrow the gender wage gap.

CHAPTER 1: INTRODUCTION

1.1 Research Background

Gender inequality refers to unequal treatment or perceptions of individuals based on gender. This inequality stems from socially constructed gender roles, cultural norms, and institutional practices that favour one gender (usually men), especially women and sexual minorities (Public Health Nigeria, 2025). There is a common misconception that gender bias is not only about inequality towards women but also includes inequality towards men. This phenomenon also leads to women pursuing power, but an ideal society should be one of gender equality, not a transition from a male-dominated society to a female-dominated society under the guise of gender equality, which is unacceptable. This study focuses on the phenomenon of inequality towards women.

Women started to be included in the development agenda in the mid-1970s, thanks to the persistent efforts of liberal feminist economists. This helped the UN adopt the Sustainable Development Goals (SDGs), which include the fifth SDG, “Promote gender equality and empower all women and girls," and the eighth SDG, “Decent work and economic growth," which increased awareness of women's issues (United Nations, 2015; Calkin, 2015). According to Pal, Piaget, Baller and Zahidi (2024), even now, the 146 countries included in this report have a worldwide gender gap score of 68.5% in 2024 and are expected to take 134 years to achieve full equality.

Gender inequality remains a serious social and economic problem in many parts of the world, particularly in regions such as South Asia and sub-Saharan Africa. South Asia includes Afghanistan, Pakistan, India, Sri Lanka, Nepal, Bangladesh, Bhutan and the Maldives. With only eight countries, South Asia has a population of 1.94 billion by 2023, with India (1.428 billion), Pakistan (240 million) and Bangladesh (172 million) as the main contributors, accounting for about 24.18% of the world's population (World Bank, 2023). South Asia ranked second last in the gender equality score, receiving 63.7 percent, below the world average of 68.5 percent. From this global ranking data, we can see that the countries in South Asia are at the back of the list, with Pakistan at the bottom of the list, even only higher than Sudan in the world (Pal et al., 2024). Sub-Saharan Africa is a region of 920 million people and has the largest number of economies of any region in the world, i.e. 35 (Pal et al., 2024a). Sub-Saharan Africa in sixth place, with a gender equality score of 68.4%, and Southern Asia in seventh place, with a gender score of 63.7%, which are both lower than the global gender parity score of 68.5% (Pal et al., 2024).

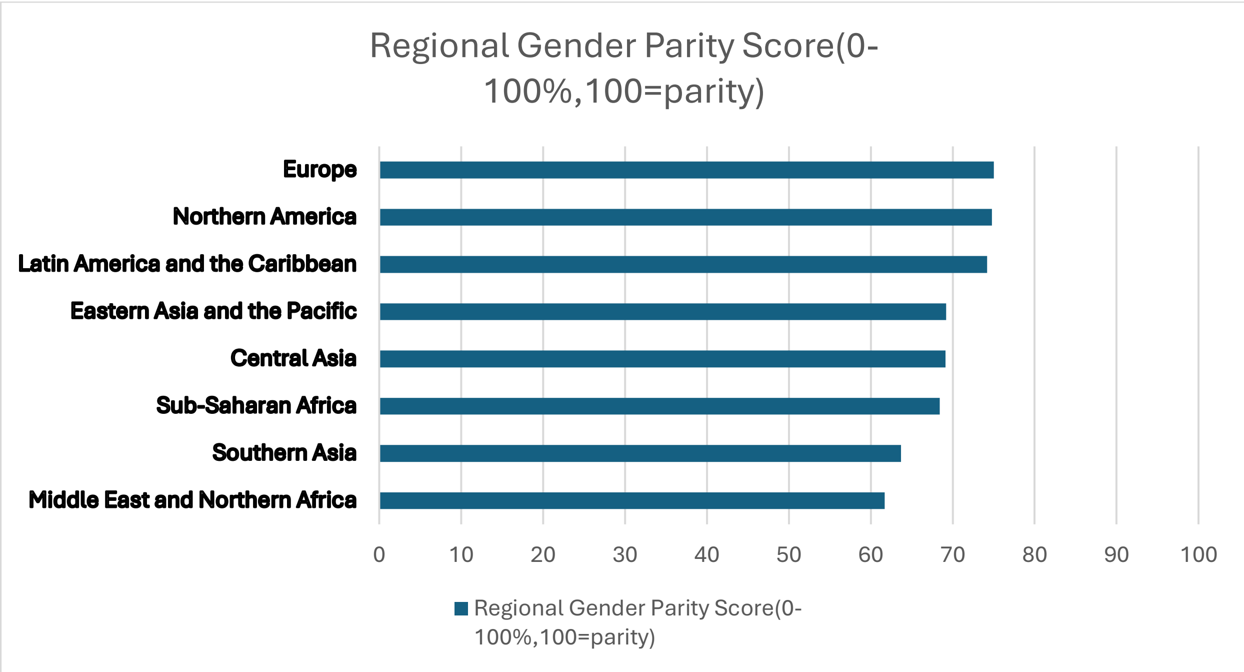

Figure 1. Regional gender parity score (0-100%,100%=parity) (Note: Population weighted average,146 countries)

Source: World Economic Forum, Global Gender Gap Report 2024

One of the most visible and dominant manifestations of this inequality is the gender wage gap, which is the persistent difference in earnings between men and women.

Despite global efforts to move towards gender equality, women in these regions still earn less than men, even when they work in similar jobs or have the same qualifications. The United Nations Development Programme (UNDP) created the GII, a composite measure of gender inequality that considers three factors: the labour market, empowerment, and reproductive health. Inequality between men and women is low when the GII score is low, and vice versa (United Nations, 2010). In many countries in South Asia and sub-Saharan Africa, high GII values reflect restrictions on women's access to education, healthcare, political representation and formal employment opportunities, which directly or indirectly affect wage differentials.

Patriarchy has always been a serious problem in sub-Saharan Africa and South Asia. Patriarchy is a hypothetical social system in which the father or male elders have absolute authority over the family or one or more men have absolute authority over other women in the community (The Editors of Encyclopaedia Britannica, 2025). Whether it is sub-Saharan Africa or South Asia, the fictitious system of patriarchy is not only not supported by law but is also strongly discouraged by law. However, this situation still exists today. Patriarchy has long been deeply rooted in the social environment of South Asia and sub-Saharan Africa, and it is impossible to separate it from the culture of these two regions (Bvukutwa, 2014). For example, it has penetrated various institutional structures, social norms, cultural customs, religious teachings, and the media's negative portrayal of gender roles, and it exists at all levels of society—namely, the family, community, workplace, and national levels (Rawat, 2014).

Under the rendering of patriarchy, people have become accustomed to a male-dominated society, exacerbating the physical differences between men and women and creating a culture where men dominate, and women obey (Sultana, 2011). Women are also at a disadvantage and are being discriminated against in the traditional division of labour. We can often hear that the deep-rooted notion in this society that women should do their homework and take care of the children is also the majority's notion, which has led to the reluctance of a minority of women to follow suit or to be condemned by social opinion. As a result, it is difficult for women to concentrate and complete their work effectively and efficiently. In South Asia and most of sub-Saharan Africa, women are accustomed to a subordinate status and are often regarded as dependents, inferior to men and in need of male support. This is a long-standing and undesirable culture that discriminates against women. Whether it is unpaid work, unpaid family help, self-employment or low-paid work, on the surface it seems that women are less capable than men, but in fact women are sacrificing for their families. It is women who take care of family members so that men can withdraw and focus fully on the workplace. However, often these sacrifices are ignored by society, resulting in discrimination against women (Sinha, 2015). These various restrictions limit women's ability to work, and coupled with the adverse effects of patriarchy, there is a certain gap between women's wages and men's wages.

According to Walby (1990), patriarchy consists of six factors that are the root causes of exploitation and are inherently interdependent. They are the family, paid employment, the state, male violence against women, sexuality and cultural institutions (Walby, 1989). The paid employment part of the above describes the patriarchal relationship at the work level, which means that women are assigned to inferior jobs and even for the same job, women's salaries are lower than men's. This is also because patriarchal relationships stem from gender inequality, and because of gender factors, there is a gender gap between men and women. For employers, women are less costly than men because women will take maternity leave throughout their lives, and coupled with the influence of a patriarchal society, employers are willing to pay less for women's salaries than for men's. Women are also more likely to accept lower wages (Sinha, 2015).

Another gender inequality phenomenon that also contributes to the gender pay gap is the representation of women in senior management in the public sector. This indicator is set in the public sector to observe the efforts made by national governments to promote gender pay equality and even gender equality. Many African countries are committed to improving the representation of women in all areas of governance in the public and private sectors (Justina Amina Bitiyong Zemo et al., 2019). Women have been consistently marginalized at the levels of power and decision-making when compared to men (Ilesanmi, 2018 & UNESCO, 2017). These are the results of a long-standing societal trend of discriminating against women and perceiving them as less intelligent than men, which belittles their abilities and social roles. South Asia also attaches great importance to this issue. Many governments in South Asia have ratified international instruments to create a society in which women and men enjoy common rights and interests, participate equally in the political, social, economic and cultural life of the country, and promote women's participation in leadership positions in local governments (Akirav, 2021). Higher responsibilities also mean higher rewards. However, when women are significantly underrepresented in these senior positions, the gender pay gap widens, and this gender inequality can suppress women's wages and career development.

1.2 Problem Statement

Gender discrimination (GD) is a type of discrimination based on gender perceptions, and it has been examined from multiple perspectives. Overall, it is believed that discrimination significantly impacts overall well-being and health (De La Torre-Pérez et al., 2022). Gender inequality and discrimination persist in various forms across global sectors, limiting women’s ability to participate equally in social and economic development. In turn, it may hinder the creation of a fair, inclusive, and prosperous society (Gupta & Kothe, 2024). One major outcome of this inequality is Workplace Gender Discrimination (WGD). WGD is a particular type of gender-based discrimination that targets people who don't conform to traditional gender roles. It has distinct and long-lasting effects on individuals’ career paths and psychological well-being (Rim & Kim, 2024). Despite notable advancements in gender inequality over the decades, women continue to face discrimination based on their gender in the workplace. This includes unequal pay, limited access to leadership roles, workplace harassment, and biased hiring and promotion policies (Kim & Oh, 2022).

In many professional settings, women remain under-represented in senior management and executive positions and often earn significantly less than their male colleagues (Bruckmüller & Braun, 2020). While progress has been made over the past 50 years, gender inequality in the workplace remains a persistent global challenge. According to recent worldwide data, only 31.7% of leadership roles are held by women, and the average wage gap between men and women is still around 20% different (Pal, K. et al., 2024). Studying the gender pay gap is essential because it reflects not only pay disparities but also broader issues related to social justice, career advancement, and equal opportunity (Bartnik et al., 2021; Javed et al., 2022).

This study focuses on Sub-Saharan Africa (SSA) and South Asia (SA). These two regions continuously face significant gender inequality and socioeconomic challenges. The decision to study these regions jointly is because SSA and SA both have large populations that heavily rely primarily on informal or subsistence economies, where labour rights and wage transparency are frequently weak or absent. Cultural and institutional restrictions in both regions limit women's access to formal work and decision-making opportunities (Fund, 2021). Both areas have high levels of informal employment and established patriarchal norms that restrict women's economic mobility. Despite some economic growth in recent decades, both SSA and SA continue to face gender inequality in labour market (Amponsah et al., 2023; Strachan & Adikaram, 2023).

In SSA, economic growth has not translated into equitable social development. Many countries in SSA failed to meet the Millennium Development Goals (MDGs), particularly those related to poverty and gender equality (Asongu et al., 2020). Firstly, according to current policy and scholarly literature, 90% of women in sub-Saharan Africa work in the informal economy (Asongu et al., 2023). Besides, Asaleye & Strydom (2024) also mentioned that the recent statistics in the International Labour Organization (ILO) have shown that female labour force participation rates are stagnant, followed by a decrease; this trend may be observed in SSA. Furthermore, women engaging in productivity activities are frequently strained by the number of available resources compared to men. Likewise, several development organizations have launched individual projects that aim to address the problem. While some of these programs have improved women's lives, a desirable end has not been achieved (Bedigen, 2022). The effects of this gender inequality phenomenon in SSA exacerbate the gender wage gap by limiting women's access to formal work opportunities, resources, and equitable remuneration, strengthening their concentration in low-paid, informal industries.

Similarly, South Asia also faces deeply rooted gender inequalities. According to the Global Gender Gap Report 2022 (World Economic Forum, 2022), the predicted time required to close the gender gap globally has increased from 100 to 132 years. South Asia is expected to take 197 years (World Economic Forum, 2022). The scale of this challenge is particularly significant given the region's large population. For instance, India alone has over 1.44 billion people, with a majority still residing in rural areas and working in agriculture (Statista, 2024). Agriculture was generally considered as an informal, seasonal, and low-paying job. In India, 76% of women work in agriculture compared to 51% of men (Strachan & Adikaram, 2023). The gender distribution in such sectors illustrates a structural imbalance where women are over-represented in low-income sectors and under-represented in formal, higher-paying occupations, deepening the gender wage gap. This phenomenon will lead the wider gender gaps.

So, due to widening and worsening gender gaps, women in South Asian developing countries are particularly impacted by status inequality issues compared to men and women in affluent nations. These discrepancies have a variety of negative effects on women's professional and financial lives (Strachan & Adikaram, 2023). According to Zaidi (2022), in Pakistan, males are portrayed as superior figures in national identities, such as leaders, military commanders, legislators, and economists, whereas females are portrayed as carers and nurturers. This establishes cultural norms, a thought pattern that encourages gender discrimination and causes disparities in society, the workplace, and the human mindset. Other than that, the female lecturers are also under-represented at a very low level, with poor incomes, limited mobility, and low places in the organisational structure compared to males. As a result, the wage gap in SA not only exists but is expected to expand unless concerted efforts are taken to overcome these structural and cultural hurdles.

Overall, many SSA and SA countries currently lack comprehensive legislation addressing workplace discrimination. The government plays a critical role in supporting women's career advancement to reduce the wage gap. According to Strachan and Adikaram (2023), labour law can ensure equal treatment, encourage a greater influx of women into the workforce, enhance their retention rates, facilitate their advancement to managerial positions, and empower them to assume influential roles. A potential solution to the wage gap is the implementation of policies such as wage transparency and reporting requirements for firms to varying degrees (Settele, 2019) and any other measures that promote gender equality. Otherwise, gender pay disparities are already narrowing in the majority of nations due to shifting demographics, particularly higher childbearing rates and lower rates of female labour force participation.

Lastly, this study provides a comprehensive analysis of the impact of gender inequality on the wage gap in Sub-Saharan Africa and South Asia. Hence, this study sheds light on the structural inequalities within the labour markets of Sub-Saharan Africa and South Asia that perpetuate wage gaps. Understanding how gender inequality manifests in different sectors, such as the underrepresentation of women in high-paying industries or leadership positions and help stakeholders develop strategies to promote gender diversity and create more inclusive work environments. Addressing these structural issues is essential to fostering a fairer labour market where both men and women have equal opportunities for success.

1.3 Research Objectives

1. To examine the impact of gender inequality on the wage gap in Sub-Saharan Africa and South Asia.

1.4 Research Questions

1. What is the impact of gender inequality on the wage gap in Sub-Saharan Africa and South Asia?

1.5 Significance of Study

Most existing research focuses on only one factors that influence the gender pay gap in Sub-Saharan Africa and South Asia countries, there is a need for more intersectional research that considers multiple factors influencing the wage gap, such as the intersection between gender inequality and vulnerable employment. This research could explore how these variables interact to exacerbate or mitigate the wage gap, providing a more comprehensive understanding of the structural barriers women face in these regions.

While plenty of research has been looking at the wage gap worldwide, relatively little of it has focused on South Asia and Sub-Saharan Africa. These regions differ significantly from other parts of the world in terms of their distinct socioeconomic, cultural, and labour market features. By offering a comprehensive understanding of how gender wage discrepancies appear in these specific places while accounting for local settings, employment types, and economic conditions, this research helps reduce this knowledge gap and provides a contribution to the literature and future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Theories

2.1.1 Occupational Segregation Theory

The Occupational Segregation Theory (OST) examines how people of different races and genders are unevenly represented in various jobs with varying wages, benefits, and working conditions. The theory suggests that certain demographic groups, such as women and racial minorities, are often overrepresented in lower-paying and less prestigious occupations. This phenomenon may be influenced by societal norms, stereotypes, and institutional barriers restricting access to higher-paying jobs (García-Mainar et al., 2017). This theory is commonly used in various aspects of labour market analysis, particularly in examining the wage gap. There is a strong relationship between occupational segregation and the wage gap, with women frequently occupying lower-paid jobs that offer less autonomy because women are often denied access to many occupations as they are limited in their options (Grybaite, 2006).

In many cases, even when women perform the same tasks as men, they are still paid less, which highlights the pervasive nature of gender inequality in the labour market (Hu & Coulter, 2023). Occupational Segregation is divided into two main components: horizontal and vertical segregation. Horizontal segregation refers to the unequal distribution of genders across different industries or sectors. For example, women are often overrepresented in care-related professions, like nursing and teaching, which are typically lower-paying, while men often dominate higher-paying fields like engineering or finance positions. Vertical segregation, on the other hand, refers to the unequal distribution of men and women within the same occupation or industry, where men tend to hold higher-paying positions, such as managerial roles, while women are relegated to lower-status, lower-paying roles. This could contribute to gender wage disparities, even within the same occupation (Gedikli, 2020).

Many studies have shown that vertical segregation plays a significant role in the wage gap and have discovered that perceptions of gender roles, biases in promotion practices, and unequal access to career advancement opportunities significantly contribute to wage disparities between men and women within the same positions (Sánchez et al., 2023). Additionally, Sánchez et al. (2023) also discovered how hierarchical structures within organizations contribute to wage disparities between men and women. Therefore, OST is appropriate and provides valuable insights to examine the relationship between gender inequality and the wage gap, highlighting the structural factors that contribute to unequal pay for equal work.

Furthermore, the ILO defines vulnerable employment based on job status, classifying own-account workers and contributing family workers as vulnerable (Lo Bue et al., 2022). Vulnerable workers are less likely to have formal employment arrangements, benefits, or social protection programs, and are more vulnerable to economic cycles. In rural areas, women are often concentrated in lower-paying, less secure jobs like agriculture or informal sectors due to occupational segregation (Kirti et al., 2024). This segregation is reinforced by traditional gender roles and societal norms, leading to fewer opportunities for advancement. As a result, women in these roles experience wage disparities, limited benefits, and less job security compared to men in more secure sectors (Chesters, 2022). OST underscores how gender-based job segregation, particularly in rural areas, contributes to the gender wage gap by restricting women’s access to higher-paying and more stable employment opportunities. This dynamic reinforces a cycle of inequality, as women are disproportionately overrepresented in low-wage, insecure, and informal employment (Gradín, 2021).

Hence, gender inequality and occupational segregation are deeply interconnected and have a long-term influence on the gender pay gap. Societal norms, discrimination, and institutional barriers all hinder women's access to higher-paying employment, resulting in a wage inequality that persists across industries and geographies.

2.1.2 Human Capital Theory

Human Capital Theory (HCT) refers to the individuals should invest in their education, skills, and experiences in order to boost their productivity. According to this theory, increasing levels of education, training, and work experience are believed to result in higher income as these investments enable an individual to improves ability to handle complex tasks, innovate, and adapt to new situations in the workforce (Eide & Showalter, 2010). However, when analysing the impact of gender in the labour market, HCT illuminates how gender inequality may affect the pay difference, particularly for women.

The Human Development Index (HDI) was launched by the United Nations Development Programme (UNDP) in 1990. It emphasized that the development of a country should take into account not only economic growth but also the well-being and capabilities of its people (Resce, 2021). It combines indicators of education, health and per capita income to provide a comprehensive view of human development and quality of life (Prajapati, 2016). Education plays a critical role in human capital, significantly influencing success in the job market and wage levels. Higher levels of education improve individuals' skills and knowledge, thereby increasing productivity and earning potential. Access to quality education creates a more skilled workforce, drives economic growth, and enhances the quality of life (Sajith & Malathi, 2020).

However, recent studies have shown a diminishing return on additional education in recent years. Even when women achieve similar or higher levels of education compared to men, they often do not receive equal financial returns, as evidenced by the wage gap (Azad & Hari, 2024). This disparity is influenced by various factors such as gender-specific job preferences, the relationship between education and wages, a lower participation rate of women in science and engineering fields, and men's higher tendency to choose these fields due to their higher earning potential. These factors contribute to job segregation and wage disparities between genders (Chowdhury et al., 2018). Furthermore, education is also correlated with improved health outcomes and higher income levels. Educated individuals have better job opportunities and higher wages, leading to enhanced living standards, as reflected in HDI (Vikram & Vanneman, 2019). Thus, the HCT provides a framework for understanding how HDI and educational achievement influence the gender wage gap. Despite significant educational progress for women, the financial returns of their education are often lower than men due to factors such as their chosen fields of study, work experience, and societal norms.

In addition, HCT also can examine the labour force participation rate. According to the HCT, maintaining a job is essential for developing experience, acquiring skills, and earning more money. However, due to the care burden and social duties, women are often limited in labour force involvement, which restricts their chances of developing new skills and advancing in their careers (Klasen, 2019). Besides, several studies have also found a positive correlation between the level of education and labour force participation rates. Higher levels of education are associated with increased engagement in the job market and vice versa. Additionally, women who return to work after taking a break may encounter challenges in catching up with their male colleagues in terms of experience and salary progression. (Sasongko et al., 2020; Langoday & Man, 2024).

The HCT emphasizes that variations in the participation rates of men and women in the labour force contribute to the gender pay gap. This occurs because women may accrue less human capital over time, resulting in enduring disparities in earnings. Women's higher rates of absence from the workforce, due to caregiving responsibilities, limit their opportunities for skill development and career advancement. Subsequently, despite similar educational achievements, gender inequality in labour force participation, career interruptions, and occupational segregation contribute significantly to the persistence of the gender wage gap. This demonstrates the impact of gender inequality on the financial rewards of education and the accumulation of human capital over time, ultimately influencing women's earning potential.

2.2 Empirical Review

Gender Inequality and Wage Gap

Gender inequality refers to the unequal distribution of rights, resources, and opportunities among genders, including men, women, boys, girls, and people with other gender identities. This inequality is the result of deeply rooted societal norms and power structures that perpetuate discrimination and unequal distribution of power and privilege. Gender disparity exacerbates the difficulties experienced by people who are already marginalised, making it an urgent problem to solve in order to attain social justice and equality (Plan International, 2025).

The wage gap refers to the difference in average earnings between men and women in the labour market, which continues to exist in most countries despite significant improvements in women's labour market participation and wages over the last few decades. While the global female-to-male wage gap has generally decreased, it has risen in some transitioning and developing economies (Wang & Cheng, 2021). Gender wage disparities persist in modern economies despite significant progress in recent decades. The gender pay gap has been extensively studied in recent decades across different countries using various methodological approaches. Overall, research indicates that the pay gap has been decreasing globally, but the pace at which male and female wages are equalizing varies (Troncoso et al., 2021).

The research emphasizes the role of between-firm inequality in contributing to the wage gap. A study focusing on the service sector found that unequal sorting of men and women into higher and lower-wage firms significantly impacts wage disparities. This analysis suggests that firm gender composition is linked to wage structures, with evidence supporting the idea of devaluation of women's work and the employment of "low road" strategies by firms that predominantly hire women (Troncoso et al., 2021). Gender inequality is a major issue in lower-middle-income nations. Gender disparity must be minimised in order to improve socioeconomic conditions. Women are frequently underpaid, according to the research, which is the primary cause of gender-based pay disparity. After that, women in the workforce face considerable salary discrimination (Dutta & Das, 2024).

2.3 Control Variables

2.3.1 Reviews on Vulnerable Employment

Vulnerable employment refers to a category of work characterized by a lack of formal employment arrangements, which often results in inadequate earnings, low productivity, and poor working conditions. Women are particularly prevalent in vulnerable employment, such as low-paying self-employment, part-time work, and informal labour, in both Sub-Saharan Africa and South Asia. The absence of stability, social safety, and legal safeguards in these sorts of employment frequently results in a large salary difference when compared to men, who are more likely to hold formal, higher-paying positions (Anon, 2024).

In addition, research shows that approximately 76% of working women in Sub-Saharan Africa are considered vulnerable workers, compared to 63% of working men. This indicates there is a significant gender disparity in the type of jobs which are open to women (Lo Bue et al., 2021). Hence, in Sub-Saharan Africa, women are more likely to have low-paying, frequently informal employment. This leads to restricted access to retirement programs and health insurance, which in turn lowers overall incomes. For example, compared to one out of ten men, one in four women are a contributing family worker. Not only that, workers in vulnerable employment, such as informal jobs, part-time work, or self-employment in low-income activities, often have fewer opportunities for training, skills development, and career advancement. Hence, women who are disproportionately represented in these roles may thus find it more challenging to move into higher-paying, more secure employment, further widening the wage gap (International Labour Organization, 2019). Thus, we can find out that there is a positive relationship between vulnerable employment and the gender pay gap in Sub-Saharan Africa and South Asia.

2.3.2 Reviews on Labour Force Participation Rate

By looking at the labour force participation rate, we can see the percentage of males and females, which helps to understand the barriers to their entry into the workforce, especially for females. In developing countries such as Sub-Saharan Africa and South Asia, in this study, labour force participation rates as well as employment rates are generally lower (Aldan, 2021). If women's labour force participation increases, it will increase downward pressure on women's wages and exacerbate the gender pay gap (Sonia R. B. & Manuel F. A., 2018). This is due to the law of supply and demand in economics, which states that when the number of labourers entering the labour market increases, the demand for jobs increases, and when the demand for something increases, the value of that something decreases, and by the same token, the “value” of a job decreases, which means that the salary decreases (Morell, 2015).

According to Schmieder, Julia, Wrohlich, and Katharina (2020), the pay gap is usually lower in countries with low female labour force participation than in countries with high female labour force participation. Encouraging more women to participate in the labour market after a gender gap has been identified can result in the labour market not being able to absorb too much labour quickly, and a phenomenon occurs in which the gender pay gap remains unchanged (Kanellopoulos & Mavromaras, 2002). The results show that the unexplained portion of the male-female wage gap is largely due to these factors affecting gender differences in participation rates (Kanellopoulos & Mavromaras, 2002).

2.3.3 Reviews on the Human Development Index

The HDI is a statistic developed and compiled by the United Nations since 1990 to measure the social and economic development levels of various countries. It is composed of four main areas of interest: mean years of schooling, expected years of schooling, life expectancy at birth, and gross national income (GNI) per capita (Investopedia Team, 2024). According to Mansha et al. (2022), human development is one of the most important factors for a country's economic growth. In countries with higher HDI, women generally have better access to education and healthcare. This, in turn, can lead to higher participation in the labour market and improved employment opportunities, enhancing their earning potential (Chowdhury et al., 2018). These factors play a role in reducing the gender wage gap. However, in some high-HDI countries, societal norms and structural barriers can still hinder women's economic progress, resulting in a smaller but persistent wage gap. On the other hand, in countries with lower HDI, the gender wage gap tends to be wider due to limited access to education, healthcare, and economic opportunities for women. This reinforces gender disparities in earnings.

Conversely, in countries with lower HDI scores, women often encounter significant obstacles to obtaining education, healthcare and participating in the economy. These challenges contribute to a wider gender wage gap and limited access to education restricts their job opportunities, often relegating them to lower-paying sectors or informal employment where wage discrimination is more prevalent (Riana & Khafid, 2022). Additionally, in less developed regions, traditional gender roles may be deeply rooted, resulting in less fair labour market practices and a lack of institutional support for gender equality (Asali & Gurashvili, 2020). The wage disparity reflects broader inequalities in human development, indicating that lower HDI scores are linked to fewer opportunities for women to achieve economic equality with men (Javed et al., 2022).

2.4 Research Gap

Most existing research focuses on only one factors that influence the gender pay gap in Sub-Saharan Africa and South Asia countries, there is a need for more intersectional research that considers multiple factors influencing the wage gap, such as the intersection between educational attainment and vulnerable employment. This research could explore how these variables interact to exacerbate or mitigate the wage gap, providing a more comprehensive understanding of the structural barriers women face in these regions.

While plenty of research has been looking at the wage gap worldwide, relatively little of it has focused on South Asia and Sub-Saharan Africa. These regions differ significantly from other parts of the world in terms of their distinct socioeconomic, cultural, and labour market features. By offering a comprehensive understanding of how gender wage discrepancies appear in these specific places while accounting for local settings, employment types, and economic conditions, this research helps reduce this knowledge gap.

2.5 Conceptual Framework

After reviewing the theories and extensions of the journal articles, we chose these variables for our research. Based on our theories mentioned in 2.1, the conceptual framework proposes the following in Figure 2.1:

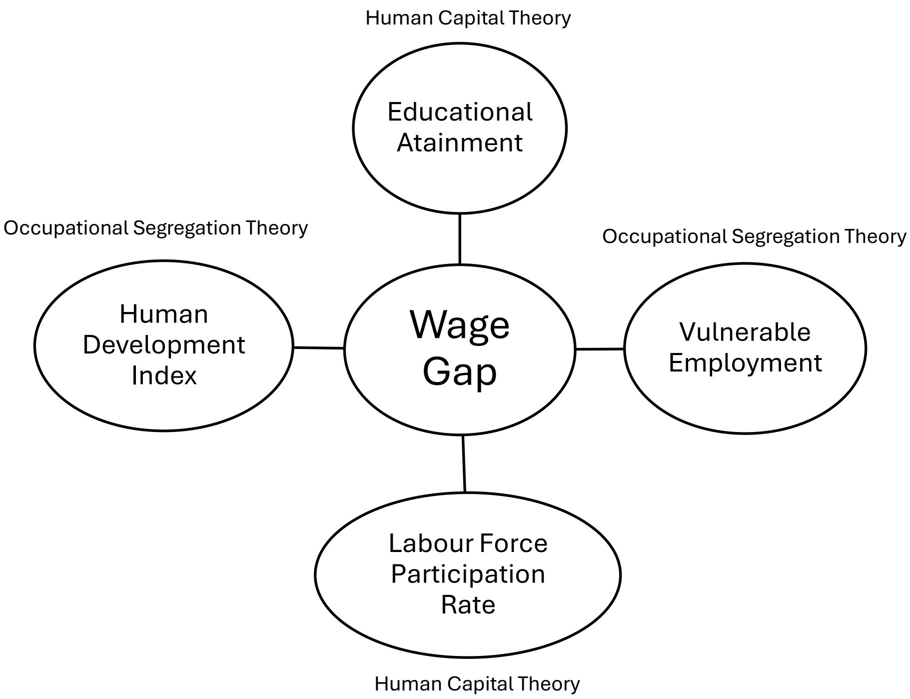

Figure 2.1: The proposed conceptual framework.

2.6 Hypothesis Testing

H_0 = Gender inequality negatively impact the wage gap

H_1 = Gender inequality positively impacts the wage gap.

CHAPTER 3: METHODOLOGY

3.1 Research Design

A research design is a systematic and rational approach to structuring and directing research to offer an appropriate framework for obtaining and assessing important data (Jain, 2023). Given how simple it is to divide the research design into qualitative and quantitative categories, this study falls into the quantitative research category. Subjective and exploratory in its approach, the qualitative study draws information from a variety of sources, including direct observation, interviews, and natural events. The primary way it differs from quantitative research is because the latter aims to produce quantitative quantifications or objective assessments of problems that it is unable to. On the other hand, controlled experiments and surveys are required to obtain objective data in quantitative research, which is statistically based and objective. It uses a variety of statistical and computational approaches to determine the causal relationships between variables. For statistical analysis, this study used quantitative research to collect objective data.

Causal research, also known as explanatory or analytical research, is a methodological strategy for determining cause-and-effect links among variables. It aims to identify whether changes in one variable (independent variable) influence changes in another variable (dependent variable) through systematic research. Our study tries to establish the connection between cause and effect between independent and dependent variables, as is common in causal research. This study examined the impact of educational attainment, vulnerable employment, and the Human Development Index on the gender pay gap in Sub-Saharan and South Asia.

3.2 Data Collection Method

Data collection is the systematic process of acquiring and analysing data for research objectives. Research and analysis use both primary and secondary data collection methods. Primary data collection, often known as first-hand information, is direct engagement with respondents to gain specific information that is relevant to the research aims. The most common procedures include surveys, questionnaires, and interviews (Cote, 2021).

Secondary data gathering involves utilizing previously collected data to achieve research objectives. Secondary data gathering is less costly and time-consuming than primary data collection, as it can be gathered from multiple sources. The researcher can use published sources, including books, academic journals, and government publications. Additionally, online databases allow access to secondary data, such as study articles and previous studies. These vital data are reviewed to provide insights that add to the existing knowledge base (Busayo Longe, 2020).

Secondary research consolidates and analyses pre-existing data to improve the credibility of studies. For this study, we used secondary data from the UNDP (United Nations Development Programme), the International Labour Organization (ILO) and the World Bank Data. We obtained books and articles from online sources, such as Google Scholar, ScienceDirect, Sage Journals and others.

3.3 Data Description

Table 3.1

Table of Proxy for each variable

Variables	Proxy Used	Source of Data
GWG	Gender ratio of wage equality for similar work	GGGR*
GI	Gender Inequality Index	UNDP**
LFPR	Labour Force Participation Rate (% of total population ages 15-64)	World Bank
HDI	Human Development Index	UNDP*
VE	Vulnerable Employment (% of total employment)	World Bank

**GGGR (Global Gender Gap Report)*

*** UNDP (United Nations Development Programmes)*

Gender ratio of wage equality for similar work: Men and women have equal rights, and the state should ensure that equality exists in practice. The elimination of the gender pay gap is addressed in Goal 8 of the Sustainable Development Goals (SDGs). Goal 8 aims to "Promote sustained, inclusive and sustainable economic growth, full and productive employment, and decent work for all by 2030." This goal is part of the United Nations' global policy set by the 2030 Development Agenda (International Labour Organization, 2024). Therefore, this indicator measures perceptions of wage equality between men and women in similar roles with comparable qualifications, skills, and responsibilities. It is generally measured on a scale of 0 to 1, with higher values indicating a smaller gender wage gap or greater wage equality (Freeland & Harnois, 2020).

Gender Inequality: We selected 23 countries from Sub-Saharan Africa and South Asia. The study uses the Gender Inequality Index (GII) from 2007 to 2021. Gender equality has become a significant topic in mainstream economics literature in recent decades and is also emphasized as crucial in achieving the SDGs, specifically Goal 5 (Nguyen, 2022). Gender inequality includes several socio-economic factors that unfairly disadvantage women, such as limited access to education, fewer high-paying job opportunities, and unequal participation in the labour market. Reducing gender inequality leads to improved access to education for women, greater chances of entering higher-paying professions, and increased representation in leadership positions. This helps to close the wage gap between men and women. So, understanding gender inequality can explain how gender inequality impacts the wage gap.

Labour Force Participation Rate: We chose 23 countries from the World Bank Group, including SSA and SA. The experiment used data from 2007 to 2021. When more women are actively involved in the workforce, the wage gap tends to decrease. This is because a higher number of women competing for jobs can lead to an increase in wages and a reduction in wage disparities. Moreover, increased participation of women in various industries, particularly those that offer higher pay, can contribute to closing the wage gap by providing women with better opportunities and fairer pay. Conversely, when women's labour force participation rate is low, it often signifies the existence of systemic barriers such as discrimination, lack of childcare, or societal norms that discourage women from working. These barriers not only limit women's economic opportunities but also contribute to a wider wage gap as women are often concentrated in lower-paying, less secure jobs (DiLek & Yildirim, 2023). Examination of labour force participation rates has been instrumental in shedding light on the correlation between gender labour participation and the wage gap."

Human Development Index: We have chosen 23 countries from Sub-Saharan Africa and South Asia and will be using the Human Development Index (HDI) from 2007 to 2021 for the experiment. Countries with higher levels of Human Development

Index (HDI) tend to have a more inclusive and robust societal framework. This is characterized by improved access to quality education, enhanced healthcare systems, and elevated income levels for their citizens. Moreover, such nations often provide greater educational and economic opportunities for both men and women, leading to a more equitable distribution of wealth and a reduction in the wage gap. As a result, the analysis of HDI clarified the relationship between HDI and the wage gap.

Vulnerable Employment: We selected 2 countries from the World Bank Group, including those in Sub-Saharan Africa and South Asia. The experiment utilized data from 2007 to 2021. In many rural areas and low-developed countries, women are more likely to work in low-skilled, part-time, or informal jobs—all of which are indicative of vulnerable employment. The wage gap is widened by these positions because they often have lower pay, fewer benefits, and fewer prospects for career progression. Women in precarious employment also have less negotiating power to demand fair salaries or improved working conditions since they lack formal contracts and job security. By examining the analysis of vulnerable employment, it becomes evident that this elucidates the crucial relationship between the wage gaps.

3.4 Econometric Model

Our research suggests an empirical model of the wage gap to gender inequality. In our study, we will use the Gender ratio of wage equality for similar work to act as the proxy for the Wage Gap. To conduct the research, we used the data from the International Labour Organization (ILO) from the years 20007 to 2021.

Equation 3.1

$$lnGWG_{it} = \beta_0 + \beta_1 GI_{it} + \beta_3 lnLFPR_{it} + \beta_4 lnHDI_{it} + \beta_5 lnVE_{it} + \varepsilon_{it}$$

Where,

$lnGWG_{it}$ = Gender Wage Gap (Gender ratio of wage equality for similar work)

β_0 = Slope Intercept

GI_{it} = Gender Inequality (gender inequality index)

$lnLFPR_{it}$ = Labour Force Participation Rate (% of total population ages 15-64) (modelled ILO estimate

$lnHDI_{it}$ = Human Development Index

$lnVE_{it}$ = Vulnerable Employment (% of total employment) (modelled ILO estimate)

ε_{it} = Error term

i = Bangladesh, India, Nepal, Pakistan, Sri Lanka, South Africa, Mauritius, Benin, Botswana, Burkina Faso, Ghana, Mali, Mauritania, Cameroon, Kenya, Malawi, Madagascar, Mozambique, Tanzania, Uganda, Zimbabwe, Lesotho, Namib

t = Year (2007, 2008, 2009, …, 2021)

We can improve the model's goodness of fit and the reliability of our results by including these four control variables（LFPR, HDI, and VE). Other researchers (Iwasaki & Satogami, 2023; Sana & Jaffri, 2021; Christl & Köppl–Turyna, 2019; Akbar, 2022) widely acknowledge these factors as having a significant long-term influence on the wage gap.

3.5 Model Estimation

Our work emphasizes using a variety of panel data models to analyse the relationship between dependent and independent variables. We intend to carefully navigate the advantages and limits of the Pooled Ordinary Least Squares (Pooled OLS), Fixed Effects Model (FEM), and Random Effects Model (REM) to arrive at persuasive results.

3.5.1 Pooled Ordinary Least Squares (Pooled OLS)

Pooled Ordinary Least Squares (Pooled OLS) is a statistical approach for analysing panel data, which includes observations from numerous entities (such as individuals, firms, or countries) over time. This technique mixes cross-sectional and time-series data, treating all observations as if they were part of a single group and ignoring any individual-specific differences. Pooled OLS assumes homogeneity across entities and eliminates entity-specific effects that could distort the study. It implies uniform features among the items being studied, simplifying the modelling process.

The five key assumptions of Ordinary Least Squares (OLS) regression are critical for obtaining accurate and reliable results. First, linearity implies that the connection between independent and dependent variables is linear. Second, no endogeneity implies that independent variables must not be linked with the error term, resulting in unbiased estimates. Third, homoscedasticity requires that the variance of the error terms be constant at all levels of the independent variables. Fourth, no autocorrelation implies that error terms should be uncorrelated with one another.

Finally, no perfect multicollinearity states that independent variables should not have perfect linear interactions with one another, allowing for the separation of their unique impacts. Violating these assumptions can result in biased or inefficient estimates, jeopardizing the validity of the regression analysis.

Equation of Pooled OLS:

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_k X_{k,it} + \mu_{it}$$

Where,

Y_{it} =dependent variable for unit i at time t

β_0 =intercept, β_1, β_2, …,

β_k=coefficients, $X_{1,it}$, $X_{2,it}$, …,

$X_{k,it}$ =independent variables for unit i at time t,

μ_{it}=error term.

In addition, the drawback of this pooling OLS is that it may not fully account for the possibility of error term correlation over time within the same cross-sectional unit, which might result in inefficiencies of estimation. This inefficiency is due to error terms that may correlate over time within the same cross-sectional unit, which could be problematic because it might result in biased standard errors and inefficient estimates. This might lead to invalid inferences or incorrect conclusions about the relationship between variables.

3.5.2 Fixed Effect Model (FEM)

Panel data analysis can benefit from fixed effects modelling, a statistical approach that accounts for unobserved individual heterogeneity. The study of fixed effects models centres on determining the common effect size, which is based on the initial assumption that all studies have (Borenstein et al., 2010). According to the fixed effects model, every single individual in the data set has a distinct intercept that doesn't change over time. Fixed-effects models effectively capture individual-specific characteristics that persist across observations and assume that differences between individuals (cross-sections) can be resolved with different intercepts (Zulfikar & STp, 2018).

The equation for FEM can be written as:

$$Y_{it} = \alpha_i + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_k X_k, i_t + \mu_{it}$$

Where α_i represents the fixed effect for the unit.

In summary, researchers should be aware of and examine the obvious limitations of this technique, even if fixed effects models provide significant advantages when it comes to controlling for time-invariant characteristics. These limitations might lead to biased results and inaccurate study conclusions, time span restrictions, low external validity, and inadequate statistical power are a few examples of these limitations (Hill et al., 2019). It is noteworthy that, as the content analysis has demonstrated, these limitations are frequently ignored in published studies, and this is a regrettable trend that might compromise the reliability and openness of the results. Researchers should endeavour to consider the benefits and drawbacks of these models at the same time, rather than ignore the weaknesses in order to raise the standard and reliability of empirical research.

3.5.3 Random Effect Model (REM)

The Random Effects Model (REM) is a statistical technique used to analyse panel data, which includes observations of many entities over time. In contrast to Fixed Effects Models (FEM), which control for time-invariant characteristics by focusing primarily on within-entity changes, REM takes into consideration both within-group and between-group variations. This is accomplished by assuming that individual-specific effects are uncorrelated with the independent variables used in the model. REM assumes that the omitted time-invariant variables do not correlate with the included time-varying covariates. This enables the model to include predictors that change over time as well as predictors that remain constant.

The model of REM can be represented as:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \mu_{it} + \epsilon_{it} Y_{it} = \beta_0 + \beta_1 X_{it} + \mu_i + \epsilon_{it}$$

Where:

Y_{it} = dependent variable

X_{it} = independent variables

μ_{it} = random effect specific to each entity

ϵ_{it} = error term

The key advantage of REM is its ability to be used both within and between variations, which makes it more efficient when the assumptions are correct. It also allows for the addition of time-invariant variables, which FEM cannot handle.

3.6 Model Selection

To evaluate the applicability of Pooled OLS, FEM, and REM models for panel data analysis, a combination of tests is typically used. The Lagrange Multiplier (LM) test and the Hausman specification test are two of the most widely utilized tests for this purpose.

3.6.1 Lagrange Multiplier (LM) test

The LM test is a diagnostic approach used in panel data analysis to identify heteroscedasticity, which occurs when the variance of error components varies across observations. This test is useful for deciding between the Pooled OLS and the REM. The test involves regressing the squared residuals from the initial regression on the explanatory factors to determine if there is a systematic relationship between the variance of error terms and independent variables. The null hypothesis of the test reveals that there is no heteroscedasticity in the data; failing to reject it means Pooled OLS is the recommended estimator. In contrast, the alternative hypothesis implies heteroscedasticity, showing that REM is preferred.

H_0 = If the variance is zero, Pooled OLS is preferred

H_1 = If the variance is not zero, REM is preferred

3.6.2 Hausman Specification Test

When choosing whether to use a fixed-effects model or a random-effects model, we can use the Hausman Specification Test to test and compare the efficiency and consistency of the FEM and the REM. The Hausman test, often referred to as the homogeneity hypothesis test, determines whether unobserved individual effects are associated with the conditional regressors in the model (Amini et al., 2012). The null hypothesis of this test is that the unobserved individual effects are exogenous, and the alternative hypothesis is that the unobserved individual effects are not exogenous. REM is preferred when the unobserved individual effects are exogenous (not reject the null hypothesis); FEM is preferred when the unobserved individual effects are not exogenous (reject the null hypothesis).

However, in order to fully utilise the performance of the Hausman Specification Test, the parameter-specified model must be correct, whereas the non-parametric Hausman test, developed in 2008, is not affected by a wrongly specified parameter model (Henderson et al., 2008).

The null and alternative hypotheses can be illustrated as follows:
H_0 = REM is preferrable
H_1 = FEM is preferrable

3.7 Diagnostic Checking

Diagnostic Checking is an important step in our research because it involves capturing observed panel data across multiple tests. These tools may detect issues such as multicollinearity, autocorrelation, and normal distribution, which are crucial for our investigation. A few diagnostic tests will be performed, including the panel unit root test, the variance inflation factor test, and the Jarque-Bera normality test. The results of all tests will be obtained using EViews 12.

3.7.1 Panel Unit Root test

Panel unit root tests are statistical methods for determining whether a panel data series is stationary or has a unit root, indicating non-stationarity. These tests are critical in time series analysis, particularly when dealing with data that spans numerous entities throughout time, because they aid in determining the best modelling strategy. Moreover, Panel unit root tests are widely applied in empirical economics and finance to analyse the properties of economic indicators, financial time series, and other longitudinal data.

H_0 = There is a unit root
H_1 = There is no unit root

Decision Making: We will reject the H_0 if the p-value of the test is smaller than the significance level at 1%, 5% or 10%. This will also mean that the variable is stationary and does not has a unit root. Otherwise, we will not reject H_0 if the p-value is larger than the significance level at 1%, 5% or 10%, which indicates the variable is not stationary and has a unit root.

3.7.2 Jarque-Bera Normality Test

The Jarque-Bera Normality Test is a statistical test used to check if a dataset follows a normal distribution. It is beneficial in evaluating the normality of the residuals in regression analysis. The test relies on sample skewness and kurtosis, comparing them to the values expected in a normal distribution. The formula for the Jarque-Bera Normality test is:

$$JB = \left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right]$$

The hypothesis testing is:

H_0 = The data is normally distributed

H_1 = The data is not normally distributed

The decision rule for the Jarque-Bera Test was to reject H_0 if the P-value is less than the significance level at 1%, 5% or 10%, meaning the data is not normally distributed. Otherwise, we do not reject H_0, meaning the data is normally distributed.

CHAPTER 4: DATA ANALYSIS

4.1 Descriptive Statistics

In this study, we analyse data collected from 23 countries over 14 years, from 2007 to 2021, with a total of 345 observations due to some omitted data. The primary objective of our descriptive statistical analysis is to explore the fundamental characteristics of the variables selected for the study. By calculating measures such as the mean, median, maximum, minimum, and standard deviation, we aim to provide a comprehensive overview of the data's central tendencies, dispersion, and overall distribution. Our main focus is on the dependent variable, the gender wage gap, which is represented by per capita food production variability. Additionally, we focus on four independent variables: Vulnerable employment, measured by the total percentage of employment; Gender Inequality Index, Human Development Index and Labour Force Participation Rate, measured by the percentage of the total population ages 15-64. By analysing these variables, we aim to better understand their impact on the gender wage gap over time in both Sub-Saharan Africa and Southern Asia.

Table 4.1

Descriptive Statistics

Variables	(WG)	(VE)	(GII)	(HDI)	(LFPR)
Mean	0.57973	4.99388	0.38013	0.39405	5.17564
Median	0.59952	5.23344	0.40579	0.37638	5.20071
Minimum	0.13012	3.17774	0.11474	0.08176	4.73065
Maximum	0.16252	5.48890	0.6025	0.78433	5.48810
Standard Deviation	0.83748	1.56087	1.15247	1.17829	1.18481
Observation	345	345	345	345	345

Note: WG - , VE - Vulnerable employment, total (% of total employment), GII – Gender Inequality Index, HDI – Human Development Index, Labour force participation rate, total (% of total population ages 15-64)

The mean value for WG is 0.57973, with a median of 0.59952, showing that the wage gap's central tendency is fairly constant across the observed countries and periods. The numbers range from a low of 0.13012 to a high of 0.16252. For example, Mauritania, from 2018 to 2020, recorded a minimum value of 0.13012, while Ghana and Lesotho both have the maximum value of 0.16252 in 2007 and 2010, respectively, reflecting slight variability. indicating substantial variation in the pay gap across the panel. The standard deviation of 0.83748 further emphasizes the low dispersion, suggesting that there is a systematic and persistent gender pay gap rather than occasional extreme disparities. This variance could be attributed to different labour market systems, cultural norms, or the implementation of gender equality regulations.

For **VE**, the average is 4.99388, and the median is 5.23344. The employment rate change ranges from 3.17774 in South Africa in 2014 to a maximum of 5.48890 in Benin in 2007. The relatively narrow range and a standard deviation of 1.56087 suggest moderate variability in employment vulnerability across observations. Despite this, the dispersion still indicates that some countries may experience significantly higher levels of insecure employment than others. Vulnerable employment, often associated with informal sector work, may reflect labour market instability and lack of social protection, which in turn could influence wage structures and economic security.

Next, the **GII** resulted in a mean of 0.38013 and a median of 0.40579, with an almost 2 times wide range from 0.11474 in Mauritius in 2019 to 0.6025 in Bangladesh in 2008 and also Mali in 2016. In addition, the standard deviation of 1.15247 reveals considerable effect in gender inequality across countries. Although the variable displays higher dispersion, the values themselves indicate that gender inequality is a persistent issue in many countries. Countries with higher GII values typically experience wider gender disparities in health, empowerment, and economic participation, which can feed into structural wage gaps.

Regarding **HDI**, the mean is 0.39405, and the median is 0.37638. The HDI ranges from a minimum of 0.08176 (Burkina Faso 2007) to a maximum of 0.78433 (Mauritius 2019). This large disparity reflects unequal access to economic opportunities, healthcare, and education—the primary HDI indicators that impact labour market outcomes and wage disparities. A standard deviation of 1.17829 indicates moderate variability in development levels, with some countries making significant progress while others lag. This suggests that wage inequality may be linked to broader developmental disparities, reinforcing the need for policies that improve human capital and economic inclusion.

Lastly, the **LFPR** has a mean of 5.17564 and a median of 5.20071. However, the gap between 4.73065 in Mauritania (2020) and 5.48810 in Tanzania (2007) highlights varying levels of workforce engagement across nations. Thus, with a standard deviation of 1.18481, LFPR exhibits considerable variation, suggesting that factors such as economic conditions, social norms, and labour policies shape workforce participation differently. Lower participation rates may contribute to weaker bargaining power and greater employment vulnerability, potentially exacerbating wage disparities.

4.2 Panel Unit Root Test

By constructing a good regression model, it is appropriate for capturing these dynamics and will be critical for assessing the long-term relationships among the chosen variables. One of its important assumptions concerns stationarity, which means that the statistical properties of a time series do not change over time. Non-stationary data leads to spurious regression results, thus misleading the interpretation and policy implications. In order to alleviate this concern, we performed a panel unit root test over our sample of 23 countries for the period 2007-2021. Indeed, this test examines the presence of unit roots in the time series data to determine whether a given series is stationary or needs differencing to achieve stationarity.

First, the first panel unit root test we use is the Levin, Lin, and Chu (LLC), which assumes the existence of a common unit root (Ali & Ali, 2008). The second test, in contrast, is the W-stat test of Im, Pesaran, and Shin (IPS), which allows for the existence of an individual unit root procedure and combines it with the individual unit root test to produce panel-specific results (Ali & Ali, 2008). After that, the remaining two tests are ADF-Fisher's chi-square test and PP-Fisher Chi-Square test. ADF-Fisher's chi-square test combines the individual series ADF tests using Fisher's method to test for unit roots in panel data, while the PP-Fisher Chi-Square test relies on the Phillips-Perron framework and assumes independent error terms, also being affected by structural breaks (Maddala & Wu, 1999).

We considered the limitations of these four tests to be different and decided to compare the results of these four tests together to ensure the stationarity of the data, since their respective results can complement each other to the greatest extent possible. Other than that, we also considered the possibility that the data may have a trend, so these tests were performed in both intercept and intercept and trend forms to avoid losing the power of the test or underestimating stationarity during testing.

Table 4.2.1

Panel Unit Root Test for Level

	Levin, Lin & Chu t*		Im, Pesaran and Shin W-stat		ADF-Fisher Chi-Square		PP-Fisher Chi-Square	
Variables	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend
WageGap	-3.6086***	-4.1269***	-1.9048**	-1.8787**	67.2992**	65.6055**	61.0399*	88.7805***
VEM	-0.4875	-3.1030***	-0.0887	-1.3256*	57.1392	68.7052**	85.5505***	63.1412**
GII	-1.7363**	-0.8786	1.9890	0.3509	28.7318	50.6083	31.8148	72.3204***
HDI	-9.1252***	3.0773	-3.3132***	6.4670	79.0058***	24.6242	129.795***	31.2435
LFPR	-1.4361*	-0.4192	3.2634	3.7372	40.8915	31.0940	49.9263	47.2013

Note. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

Table 4.2.2

Panel Unit Root Test for First Difference

	Levin, Lin & Chu t*		Im, Pesaran and Shin W-stat		ADF-Fisher Chi-Square		PP-Fisher Chi-Square	
Variables	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend
WageGap	-7.4065***	-6.2954***	-7.0044***	-4.1831***	135.278***	100.701***	274.531***	260.547***
VEM	-7.1798***	-6.2471***	-5.0717***	-2.2784**	107.032***	75.1936***	168.624***	138.846***
GII	-3.2259***	-2.2199**	-4.6141***	-2.4737***	98.2479***	71.1461**	271.133***	229.329***
HDI	3.6412	-2.2641**	1.2836	-1.6516**	41.3900	60.5319*	92.2135***	132.683***
LFPR	2.3827	6.8232	0.3678	0.9405	41.5309	37.3318	162.974***	164.850***

Note. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

Table 4.2.3

Panel Unit Root Test for Second Difference

	Levin, Lin & Chu t*		Im, Pesaran and Shin W-stat		ADF-Fisher Chi-Square		PP-Fisher Chi-Square	
Variables	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend
WageGap	-14.1418***	-12.3829***	-11.7747***	-7.9368***	207.909***	147.705***	464.146***	379.882***
VEM	-5.3870***	-2.1013**	-7.7063***	-4.6253***	148.756***	105.486***	335.204***	271.912***
GII	-4.6171***	-3.1509***	-9.6825***	-6.7323***	175.812***	129.953***	460.602***	383.282***
HDI	-11.0683***	-9.4671***	-8.3054***	-6.2293***	141.320***	114.235***	312.994***	292.967***
LFPR	7.6730	8.4466	-5.5301***	-3.0990***	114.084***	85.4493***	365.394***	324.952***

Note. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

The above are the results of the unit root test for the panel unit root test. The test results for both tables are based on log-transformed variables, including WageGap, VEM, GII, HDI and LFPR. Table 4.2.1 is the panel unit root test for level, Table 4.2.2 is the panel unit root test for first difference and Table 4.2.3 is the panel unit root test for second difference. The first difference result in Table 4.2.1 shows the dynamic changes of these variables over time. We convert the data to the natural logarithm form to make data more likely to be stationary. In addition, when skewed data is usually generated in actual research, and analysis of these data will produce invalid results, we can ensure the accuracy of the data and the analysis of the results by means of a logarithmic transformation to convert the skewed data to approximately normally distributed data (Feng et al., 2014).

According to the results in Table 4.2.1.1, only the Wage Gap is strongly stationary across all tests and specifications. Specifically, the LLC test shows that the intercept is –3.6086 and the trend is –4.1269, both of which are significant at the 1% level, and the IPS, ADF-Fisher and PP-Fisher tests also provide supporting evidence. This indicates that the wage gap is stationary, i.e. I(0). The HDI shows magnitude of large (–9.1252***) in the LLC test and significant in intercept only in the other tests, which indicates that the HDI is stationary around a constant mean rather than a deterministic linear trend in level test. The VEM is the opposite of the HDI in the level test and is significant in intercept & trend specifications in all four tests, only in PP-Fisher Chi-Square test that is significant in intercept only and Intercept & trend specifications at the same time, which indicates that the mean of the VEM changes over time in a predictable way (trend-stationary). GII and LFPR are not significant in most level tests and are not uniform, indicating that both GII and LFPR have unit roots.

After the first difference processing in Table 4.2.1.2, the wage gap remains as significant in all tests and specifications as it was in the level test. The VEM and GII, on the other hand, change to significance in all tests and specifications after the first difference. This pattern suggests that the VEM and GII variables show trend-stationarity, and the overall evidence supports that VEM and GII are stationary at first difference, or I(1). Other than that, the HDI intercept & trend specifications were significant in all four tests, which indicates that the HDI has significant trend characteristics. LFPR is only significant in intercept only and intercept & trend specification of PP-Fisher Chi-Square; it shows that LFPR has a possible unit root in the first differencing level.

All variables in second difference (Table 4.2.1.3) are significant in intercept only and intercept & trend specification of all tests except for the LFPR variable under LLC test. HDI are stationary at second difference, or I(2). LFPR variable is supported by a major panel unit root test that it is not a unit root process, and its non-significance could be due to the assumption of a common unit root across all cross-sections.

4.3 Pooled OLS, Fixed Effect Model (FEM), Random Effect Model (REM), and Diagnostic Tests

Long Run Regression & Specification Tests

	Pooled OLS	FEM	REM
C	-2.06910***	-0.97483	-1.89222***
	(0.15862)	(0.68755)	(0.34896)
lnVE	0.00549	-0.40778***	-0.11418***
	(0.01548)	(0.13498)	(0.03759)
lnLFPR	0.39207***	0.49592***	0.44564***
	(0.03599)	(0.12072)	(0.08220)
lnHDI	0.03381	-0.43987***	-0.29073***
	(0.06485)	(0.13284)	(0.10918)
lnGII	-0.01650	0.24870*	0.17586
	(0.07314)	(0.12872)	(0.11253)
No. of Observation	345	345	345
R^2	0.28255	0.70642	0.19783
Adj R^2	0.27411	0.68242	0.18839
Poolability F-Test	-	-	33.4748***
BPLM Test	-	-	544.5054***
Hausman Test	-	21.6786***	-

Diagnostic tests

Autocorrelation Test *(Durbin Watsons)*	1.895

This research started by estimating the data using the pooled ordinary least square (POLS) model, where most of the variables significantly influenced the gender wage gap (WG). However, Pooled OLS assumes all entities are identical, leading to biased estimates by ignoring individual differences. It suffers from omitted variable bias, ignores panel effects, and assumes constant variance. This makes it unsuitable when fixed or random effects exist, limiting its use in this research analysis. As a result, we then used panel data models, such as the fixed effect model (FEM) and the random effect model (REM), to examine the wage gap.

Firstly, the F-test comparing FEM and Pooled OLS returned a significant Prob(F-statistic) of 0.0000, leading to rejection of the null hypothesis. This confirms that FEM is statistically superior to Pooled OLS, as it effectively controls for unobserved, time-invariant heterogeneity across countries. Next, the Breusch-Pagan Lagrangian Multiplier (BP-LM) test was used to compare Pooled OLS and REM. The test also yielded a significant p-value of 0.0000, leading to rejection of the null hypothesis and indicating that REM is preferable to Pooled OLS.

Furthermore, the Hausman test was conducted to choose between FEM and REM. The test results led to rejection of the null hypothesis, suggesting that FEM is more appropriate due to the correlation between the individual effects and explanatory variables. Thus, the FEM outperformed the other models with a higher adjusted R-squared of 0.6824, indicating strong explanatory power. Significant predictors of the wage gap include the Labour Force Participation Rate (coefficient = 0.4959), Human Development Index (coefficient = -0.4399), and Vulnerable Employment (coefficient = -0.4078), while the Gender Inequality Index was marginally significant (coefficient = 0.2487). In conclusion, based on statistical testing and model performance, the Fixed Effects Model (FEM) is the most appropriate and reliable model for estimating the gender wage gap in this panel data context.

In panel data analysis, testing for autocorrelation is important because it can affect the efficiency of estimators and the accuracy of standard errors. According to the result, which uses panel data to examine how gender-related characteristics contribute to the explanation of the pay gap in South Asia and Sub-Saharan Africa, the Durbin-Watson (DW) statistic is 1.895. The DW value indicates that there is no substantial autocorrelation between the regression model's residuals because it is around the optimal benchmark of 2. This indicates that there is not a lot of serial correlation, which is the relationship between error terms from different periods.

Testing for autocorrelation is particularly important in panel data analysis, if serial correlation were present, it could lead to biased standard errors and reduce the reliability of hypothesis testing. However, since the DW statistic falls within the acceptable range, we can be more confident that the relationship between gender inequality, human development, labour participation, vulnerable employment, and the gender wage gap is not distorted by autocorrelation issues. This strengthens the credibility and validity of our regression results.

4.4 Study Findings

Main Variables	P-value	Coefficient	Research Findings
Vulnerable Employment	0.0027	-0.40778	Significant Negative
Labour Force Participation Rate	0.0001	0.49592	Significant Positive
Human Development Index	0.0010	-0.43987	Significant Negative
Gender Inequality Index	0.0542	0.24870	Significant Positive

For vulnerable employment, we expected it to have a statistically significant positive relationship with the wage gap. Our findings decline this expectation, showing a significant negative relationship ($\beta = -0.408$, $p < 0.01$), holding other variables constant, a one unit increase in vulnerable employment leads to a 0.40778 unit decrease in the outcome. suggesting that higher levels of vulnerable

employment are associated with a narrower wage gap. This may be due to the nature of informal work, which tends to exhibit smaller gender-based wage differences.

We also expected the labour force participation rate to have a significant relationship with the wage gap. The results show a significant positive relationship ($\beta = 0.496$, $p < 0.01$), holding other variables constant, a unit increase in the participation rate leads to a 0.49592 unit increase in the dependent variable. indicating that as more women enter the labour market, the wage gap may widen. This finding could reflect structural barriers and unequal pay systems that persist despite higher female participation.

For the Human Development Index, a negative relationship with the wage gap was expected. The model supports this, revealing a significant negative relationship ($\beta = -0.440$, $p < 0.01$), this implies that for every one unit increase in HDI, the dependent variable decreases by 0.43987 units, which may seem counterintuitive, consistent with the idea that higher development levels contribute to more equitable wage distribution. Our findings have shown a negative relationship, which can be supported by the findings conducted by World Bank Group (2023), which also concluded the negative relationship between Human Development Index and gender wage gap.

The Gender Inequality Index has a positive and marginally significant relationship with the gender wage gap, with a coefficient of $\beta = 0.2487$ and a p-value of 0.0542. This suggests that higher gender inequality is associated with a wider gender wage gap. Although the result is not statistically significant at the 5% level, it is significant at the 10% level, indicating that countries with greater disparities in areas such as political empowerment and labour market participation tend to exhibit larger wage gaps between men and women. This result can be supported by González et al. (2022), as it mentioned that gender norms influence the gender wage gap and broader gender inequalities can exacerbate wage disparities.

Interestingly, the result for vulnerable employment contradicts the expectations set by previous literature. While existing studies including Lo Bue et al. (2021) and the International Labour Organization (2019)—indicate a positive relationship between vulnerable employment and the gender wage gap, our regression result shows a significant negative coefficient (-0.40778), suggesting that an increase in vulnerable employment is associated with a decrease in the gender wage gap.

This contradiction may stem from several factors, most notably the level of data aggregation used in our analysis. Our study uses country-level panel data for Sub-Saharan Africa and South Asia, which might mask gender-specific disadvantages within countries. In many developing economies, both men and women participate heavily in the informal sector. Therefore, when vulnerable employment increases, it may reflect broader informal economic activity affecting both genders, rather than specifically capturing female disadvantage. As a result, the gender-based differences in wage outcomes may appear to narrow, not because women are better off, but because men are equally exposed to low-wage, unstable jobs, thus reducing the measured gap.

Similar observations were noted by Razavi et al. (2012), who argued that aggregate-level labour statistics often fail to reveal the intersectional vulnerabilities experienced by women, especially when both men and women are increasingly pushed into informal employment. In such cases, the relative gap may decrease, but only because men’s earnings are also falling, not because women's economic conditions have improved. Thus, while our result does not align with the previous literature in terms of the direction of the relationship, it may still reflect underlying labour market dynamics in regions where informality is widespread and economic vulnerability is high for all.

For the labour force participation rate, the regression result aligns with studies such as Sonia and Manuel (2018) and Schmieder et al. (2020), which suggest that an increase in labour participation can sometimes lead to downward pressure on wages. This is particularly relevant in developing regions like Sub-Saharan Africa and South Asia, where a rapid rise in labour supply especially if not matched by job creation can exacerbate wage disparities. These findings reinforce the notion that higher participation alone is not sufficient to close the gender wage gap without structural improvements in job quality and equal opportunity.

Similarly, the findings for the human development index (HDI) also support prior literature, which highlights that while higher HDI is often associated with improved access to education and healthcare for women, it does not automatically translate into wage equality. As noted by Chowdhury et al. (2018) and Javed et al. (2022), deep-rooted social norms and labour market structures can continue to hinder women's economic progress even in more developed settings. Therefore, the persistence of the wage gap in high HDI countries is consistent with the argument that development must be accompanied by targeted gender-equality policies to be effective.

CHAPTER 5: CONCLUSION

5.1 Summary and Policy Implications

In summary, this study examined the role of gender concerning wage gaps in two culturally and structurally unequal regions: Sub-Saharan Africa (SSA) and South Asia (SA). Using panel data from 23 countries from 2007 to 2021, this study drew on the Occupational Segregation Theory and the Human Capital Theory to explore how educational achievement, labour force participation, vulnerable employment, and the Human Development Index constitute the gender wage gap.

Gender inequality has a significant effect on wage differentials. Descriptive and econometric analyses showed that most women spend much time in vulnerable employment, are less represented in high-paying jobs and leadership, and suffer from deeply entrenched cultural norms and discriminatory practices that lower their pay. Panel data estimation using Pooled OLS, Fixed Effects, and Random Effects models further established that gender inequality has a positive relationship with wage differentials in both SSA and SA. After that, the findings suggest that women in both regions frequently receive lower wages than men for work comparable to theirs, not because of any differential capabilities or productivity but due to economic mobility restrictions imposed by social structures. Moreover, issues such as patriarchal norms, reduced access to education, informal labour markets, and underrepresentation in decision-making further increase this gap.

This paper adds to the literature on cross-regional comparison and rigorous empirical analysis of wage inequality due to gender-based differences. There are many nascent policies, such as equal pay legislation, pay transparency, and leadership programs fostering female labour supply, intended to close the gap.

Subsequent models can be extended with more dynamic indicators and discuss sectoral disparities.

The findings of this study underscore the need for policy intervention to address gender inequality because it may affect the gender wage gap in SSA and SA. The government should increase the investment in women's human capital. Gender inequality in access to work, education, and health care restricts women's capacity to profit from structural economic improvements, resulting in a wider wage difference. This is especially visible in countries that still rely on subsistence agriculture, where women are frequently restricted to low-wage, informal sectors. Moreover, the government can also implement Education Plus and strongly focus on promoting the importance of girls' education. Therefore, the program seeks to address and modify cultural norms that limit educational options for women and contribute to occupational segregation to ensure that they obtain quality education. Hence, increasing women's human capital can increase the demand for female labour and generate positive spillover effects, narrowing the gender wage gap.

5.2 Recommendations for Future Research

We recommend that future researchers focus more on the issues surrounding data quality and availability, particularly when studying emerging regions like South Asia and Sub-Saharan Africa. Our experience shows that the uneven availability of gender-disaggregated economic data is one of the main obstacles to performing thorough cross-country analysis. This problem not only restricts the analysis's range but also runs the risk of skewing the results because it leaves out nations with inadequate or missing datasets.

Thus, we recommend that future researchers explore alternative or supplementary sources of data beyond publicly available online databases. Collaborations with national statistics departments, regional research institutions, and international organizations, such as the World Bank, United Nations Development Programme (UNDP), International Labour Organization (ILO), and UN Women, may offer access to more detailed and updated datasets that are not readily accessible to the public. These partnerships can also support the development of more targeted and region-specific indicators that reflect the unique economic and social dynamics of gender and labour in each country.

Furthermore, we advise using a mixed-method approach that blends qualitative findings from surveys, interviews, and case studies with quantitative panel data analysis. Especially for nations with little statistical capacity, this will help fill in important gaps and provide context when data is inconsistent or missing. These qualitative elements can also improve the way quantitative results are interpreted and provide insight into institutional or cultural issues that affect pay gaps and that are not entirely explained by data individually.

By implementing these recommendations, future research will be better positioned to present more accurate, inclusive, and policy-relevant findings that reflect the full diversity and complexity of wage gap trends across the entire Sub-Saharan Africa and South Asia regions.

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Appendices

Appendix 4.1 Descriptive Statistics

	A	B	C	D	E	F
1		(WG)	(VE)	(GII)	(HDI)	(LFPR)
2						
3	Mean	-0.42027	3.99388	-0.61987	-0.60595	4.17564
4	Median	-0.40048	4.23344	-0.59421	-0.62362	4.20071
5	Minimum	-0.86988	2.17774	-1.11474	-1.08176	3.73065
6	Maximum	-0.16252	4.48890	-0.39750	-0.21567	4.48810
7	Standard Deviation	0.13350	0.56087	0.15247	0.17829	0.18481
8	Observation	345	345	345	345	345
9						
10						
11						
12	Standard Error	0.007187348	0.030196043	0.008208842	0.009598895	0.009949682
13						

Appendix 4.2: Panel Unit Root Test in Level with Intercept

Panel unit root test: Summary
Series: WAGE_GAP__WG_
Date: 04/06/25 Time: 16:15
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.60858	0.0002	23	299
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.90482	0.0284	23	299
ADF - Fisher Chi-square	67.2992	0.0219	23	299
PP - Fisher Chi-square	61.0399	0.0679	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: VULNERABLE_EMPLOYMENT__VE_
Date: 04/06/25 Time: 16:17
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.48750	0.3130	23	299
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.08870	0.4647	23	299
ADF - Fisher Chi-square	57.1392	0.1256	23	299
PP - Fisher Chi-square	85.5505	0.0004	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LABOUR_FORCE_PARTICIPATUION_RAT
Date: 04/06/25 Time: 16:18
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.43614	0.0755	23	299
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	3.26343	0.9994	23	299
ADF - Fisher Chi-square	40.8915	0.6856	23	299
PP - Fisher Chi-square	49.9263	0.3201	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: HUMAN_DEVELOPMENT_INDEX__HDI_
Date: 04/06/25 Time: 16:20
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-9.12522	0.0000	23	299
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.31316	0.0005	23	299
ADF - Fisher Chi-square	79.0058	0.0018	23	299
PP - Fisher Chi-square	129.795	0.0000	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: GENDER_INEQALITY_INDEX__GII_
Date: 04/06/25 Time: 16:22
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.73628	0.0413	23	299
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.98897	0.9766	23	299
ADF - Fisher Chi-square	28.7318	0.9784	23	299
PP - Fisher Chi-square	31.8148	0.9446	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.2.1: Panel Unit Root Test in Level with Intercept and Trend

Panel unit root test: Summary
Series: WAGE_GAP__WG_
Date: 04/06/25 Time: 16:16
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.12688	0.0000	23	299
Breitung t-stat	-2.17929	0.0147	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.87872	0.0301	23	299
ADF - Fisher Chi-square	65.6055	0.0303	23	299
PP - Fisher Chi-square	88.7805	0.0002	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: VULNERABLE_EMPLOYMENT__VE_
Date: 04/06/25 Time: 16:17
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.10296	0.0010	23	299
Breitung t-stat	0.86906	0.8076	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.32555	0.0925	23	299
ADF - Fisher Chi-square	68.7052	0.0166	23	299
PP - Fisher Chi-square	63.1412	0.0473	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LABOUR_FORCE_PARTICIPATUION_RAT
Date: 04/06/25 Time: 16:19
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.41923	0.3375	23	299
Breitung t-stat	4.94817	1.0000	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	3.73715	0.9999	23	299
ADF - Fisher Chi-square	31.0940	0.9546	23	299
PP - Fisher Chi-square	47.2013	0.4232	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: HUMAN_DEVELOPMENT_INDEX__HDI_
Date: 04/06/25 Time: 16:21
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	3.07727	0.9990	23	299
Breitung t-stat	8.06929	1.0000	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	6.46701	1.0000	23	299
ADF - Fisher Chi-square	24.6242	0.9959	23	299
PP - Fisher Chi-square	31.2435	0.9527	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: GENDER_INEQALITY_INDEX__GII_
Date: 04/06/25 Time: 16:23
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.87856	0.1898	23	299
Breitung t-stat	0.27186	0.6071	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.35087	0.6372	23	299
ADF - Fisher Chi-square	50.6083	0.2966	23	299
PP - Fisher Chi-square	72.3204	0.0079	23	322

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.2.2: Panel Unit Root Test in First Difference with Intercept

Panel unit root test: Summary
Series: D(WAGE_GAP__WG_)
Date: 04/06/25 Time: 16:16
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.40650	0.0000	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-7.00443	0.0000	23	276
ADF - Fisher Chi-square	135.278	0.0000	23	276
PP - Fisher Chi-square	274.531	0.0000	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(VULNERABLE_EMPLOYMENT__VE_)
Date: 04/06/25 Time: 16:17
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.17981	0.0000	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-5.07171	0.0000	23	276
ADF - Fisher Chi-square	107.032	0.0000	23	276
PP - Fisher Chi-square	168.624	0.0000	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LABOUR_FORCE_PARTICIPATUION_RAT)
Date: 04/06/25 Time: 16:18
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	2.38273	0.9914	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.36778	0.6435	23	276
ADF - Fisher Chi-square	41.5309	0.6598	23	276
PP - Fisher Chi-square	162.974	0.0000	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(HUMAN_DEVELOPMENT_INDEX__HDI_)
Date: 04/06/25 Time: 16:20
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	3.64119	0.9999	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.28360	0.9004	23	276
ADF - Fisher Chi-square	41.3900	0.6655	23	276
PP - Fisher Chi-square	92.2135	0.0001	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(GENDER_INEQALITY_INDEX__GII_)
Date: 04/06/25 Time: 16:22
Sample: 2007 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.22593	0.0006	23	276
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.61409	0.0000	23	276
ADF - Fisher Chi-square	98.2479	0.0000	23	276
PP - Fisher Chi-square	271.133	0.0000	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.2.3: Panel Unit Root Test in First Difference with Intercept and Trend

Panel unit root test: Summary
Series: D(WAGE_GAP__WG_)
Date: 04/06/25 Time: 16:17
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.29542	0.0000	23	276
Breitung t-stat	-3.41141	0.0003	23	253
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.18312	0.0000	23	276
ADF - Fisher Chi-square	100.701	0.0000	23	276
PP - Fisher Chi-square	260.547	0.0000	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(VULNERABLE_EMPLOYMENT__VE_)
Date: 04/06/25 Time: 16:18
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.24711	0.0000	23	276
Breitung t-stat	-1.14031	0.1271	23	253
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.27843	0.0114	23	276
ADF - Fisher Chi-square	75.1936	0.0042	23	276
PP - Fisher Chi-square	138.846	0.0000	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LABOUR_FORCE_PARTICIPATUION_RAT)
Date: 04/06/25 Time: 16:19
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	6.82319	1.0000	23	276
Breitung t-stat	1.94714	0.9742	23	253
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.94047	0.8265	23	276
ADF - Fisher Chi-square	37.3318	0.8151	23	276
PP - Fisher Chi-square	164.850	0.0000	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(HUMAN_DEVELOPMENT_INDEX__HDI_)
Date: 04/06/25 Time: 16:22
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.26409	0.0118	23	276
Breitung t-stat	2.43157	0.9925	23	253
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.65159	0.0493	23	276
ADF - Fisher Chi-square	60.5319	0.0739	23	276
PP - Fisher Chi-square	132.683	0.0000	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(GENDER_INEQALITY_INDEX__GII_)
Date: 04/06/25 Time: 16:23
Sample: 2007 2021
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.21987	0.0132	23	276
Breitung t-stat	-2.70492	0.0034	23	253
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.47368	0.0067	23	276
ADF - Fisher Chi-square	71.1461	0.0101	23	276
PP - Fisher Chi-square	229.329	0.0000	23	299

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.3: Pooled Ordinary Least Square (Pooled OLS)

Dependent Variable: WAGE_GAP__WG_
Method: Panel Least Squares
Date: 03/20/25 Time: 09:11
Sample: 2007 2021
Periods included: 15
Cross-sections included: 18
Total panel (balanced) observations: 270

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.907410	0.189252	-10.07868	0.0000
VULNERABLE_EMPLOYMENT__VE_	-0.025449	0.021525	-1.182326	0.2381
LABOUR_FORCE_PARTICIPATUION_R...	0.435583	0.054069	8.055992	0.0000
HUMAN_DEVELOPMENT_INDEX__HDI_	0.112298	0.068904	1.629759	0.1043
GENDER_INEQALITY_INDEX__GII_	0.261723	0.091577	2.857954	0.0046

R-squared	0.244773	Mean dependent var	-0.394313
Adjusted R-squared	0.233374	S.D. dependent var	0.128133
S.E. of regression	0.112190	Akaike info criterion	-1.518903
Sum squared resid	3.335441	Schwarz criterion	-1.452265
Log likelihood	210.0519	Hannan-Quinn criter.	-1.492144
F-statistic	21.47202	Durbin-Watson stat	0.346801
Prob(F-statistic)	0.000000		

Appendix 4.3.1: Fixed Effect Model (FEM)

Dependent Variable: WAGE_GAP__WG_
Method: Panel Least Squares
Date: 03/20/25 Time: 09:17
Sample: 2007 2021
Periods included: 15
Cross-sections included: 18
Total panel (balanced) observations: 270

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.104301	0.714272	-1.546052	0.1234
VULNERABLE_EMPLOYMENT__VE_	-0.212719	0.155996	-1.363625	0.1739
LABOUR_FORCE_PARTICIPATUION_R...	0.312938	0.131232	2.384614	0.0178
HUMAN_DEVELOPMENT_INDEX__HDI_	-0.623751	0.142154	-4.387842	0.0000
GENDER_INEQALITY_INDEX__GII_	0.275364	0.154462	1.782724	0.0759

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.676040	Mean dependent var	-0.394313
Adjusted R-squared	0.648608	S.D. dependent var	0.128133
S.E. of regression	0.075955	Akaike info criterion	-2.239374
Sum squared resid	1.430763	Schwarz criterion	-1.946169
Log likelihood	324.3155	Hannan-Quinn criter.	-2.121636
F-statistic	24.64410	Durbin-Watson stat	0.797429
Prob(F-statistic)	0.000000		

Appendix 4.3.2: Random Effect Model (REM)

Dependent Variable: WAGE_GAP__WG_
Method: Panel EGLS (Cross-section random effects)
Date: 03/20/25 Time: 09:18
Sample: 2007 2021
Periods included: 15
Cross-sections included: 18
Total panel (balanced) observations: 270
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.783554	0.388385	-4.592226	0.0000
VULNERABLE_EMPLOYMENT__VE_	-0.150210	0.039835	-3.770775	0.0002
LABOUR_FORCE_PARTICIPATUION_R...	0.460177	0.097831	4.703793	0.0000
HUMAN_DEVELOPMENT_INDEX__HDI_	-0.374353	0.116566	-3.211504	0.0015
GENDER_INEQALITY_INDEX__GII_	0.330794	0.135382	2.443406	0.0152

Effects Specification		S.D.	Rho
Cross-section random		0.085270	0.5576
Idiosyncratic random		0.075955	0.4424

Weighted Statistics			
R-squared	0.253756	Mean dependent var	-0.088383
Adjusted R-squared	0.242492	S.D. dependent var	0.089224
S.E. of regression	0.077656	Sum squared resid	1.598082
F-statistic	22.52796	Durbin-Watson stat	0.719216
Prob(F-statistic)	0.000000		

Unweighted Statistics			
R-squared	0.022268	Mean dependent var	-0.394313
Sum squared resid	4.318130	Durbin-Watson stat	0.266172

Appendix 4.3.3 Breusch-Pagan Lagrange Multiplier Test (BPLM)

Lagrange Multiplier Tests for Random Effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided (all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	363.5685 (0.0000)	13.12372 (0.0003)	376.6922 (0.0000)
Honda	19.06747 (0.0000)	3.622668 (0.0001)	16.04435 (0.0000)
King-Wu	19.06747 (0.0000)	3.622668 (0.0001)	15.49645 (0.0000)
Standardized Honda	22.69553 (0.0000)	3.932521 (0.0000)	13.86782 (0.0000)
Standardized King-Wu	22.69553 (0.0000)	3.932521 (0.0000)	13.18505 (0.0000)
Gourieroux, et al.	--	--	376.6922 (0.0000)

Appendix 4.3.4: Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	16.002178	4	0.0030

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
VULNERABLE_EMPLOYMENT__VE_	-0.212719	-0.150210	0.022748	0.6785
LABOUR_FORCE_PARTICIPATUION_R...	0.312938	0.460177	0.007651	0.0923
HUMAN_DEVELOPMENT_INDEX__HDI_	-0.623751	-0.374353	0.006620	0.0022
GENDER_INEQALITY_INDEX__GII_	0.275364	0.330794	0.005530	0.4561

Cross-section random effects test equation:
Dependent Variable: WAGE_GAP__WG_
Method: Panel Least Squares
Date: 03/20/25 Time: 09:19
Sample: 2007 2021
Periods included: 15
Cross-sections included: 18
Total panel (balanced) observations: 270

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.104301	0.714272	-1.546052	0.1234
VULNERABLE_EMPLOYMENT__VE_	-0.212719	0.155996	-1.363625	0.1739
LABOUR_FORCE_PARTICIPATUION_R...	0.312938	0.131232	2.384614	0.0178
HUMAN_DEVELOPMENT_INDEX__HDI_	-0.623751	0.142154	-4.387842	0.0000
GENDER_INEQALITY_INDEX__GII_	0.275364	0.154462	1.782724	0.0759

Effects Specification

Cross-section fixed (dummy variables)			
R-squared	0.676040	Mean dependent var	-0.394313
Adjusted R-squared	0.648608	S.D. dependent var	0.128133
S.E. of regression	0.075955	Akaike info criterion	-2.239374
Sum squared resid	1.430763	Schwarz criterion	-1.946169
Log likelihood	324.3155	Hannan-Quinn criter.	-2.121636
F-statistic	24.64410	Durbin-Watson stat	0.797429
Prob(F-statistic)	0.000000		

Appendix 4.3.5: Autocorrelation Test (Durbin-Watson)

Dependent Variable: RESID01
Method: Panel Least Squares
Date: 04/09/25 Time: 23:39
Sample (adjusted): 2008 2021
Periods included: 14
Cross-sections included: 23
Total panel (balanced) observations: 322

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.035966	0.087282	-0.412067	0.6806
RESID_LAG	0.851601	0.030068	28.32291	0.0000
GENDER_INEQALITY_INDEX__GII_	0.008112	0.040304	0.201270	0.8406
HUMAN_DEVELOPMENT_INDEX__HDI_	0.020755	0.036499	0.568639	0.5700
LABOUR_FORCE_PARTICIPATUION_R...	0.002002	0.019734	0.101448	0.9193
VULNERABLE_EMPLOYMENT__VE_	0.010094	0.008521	1.184682	0.2370

R-squared	0.717792	Mean dependent var	-0.003067
Adjusted R-squared	0.713327	S.D. dependent var	0.112546
S.E. of regression	0.060259	Akaike info criterion	-2.761856
Sum squared resid	1.147460	Schwarz criterion	-2.691523
Log likelihood	450.6589	Hannan-Quinn criter.	-2.733777
F-statistic	160.7483	Durbin-Watson stat	1.895381
Prob(F-statistic)	0.000000		