Inequality, Education and Occupational Change in the Philippines

Nadia Belhaj Hassine[1], Francine Claire Fernandez[2] and Benjamin Aaron Lavin[3]

https://doi.org/10.62345/jads.2025.14.3.1

Abstract

The Philippines has made considerable progress in reducing poverty; however, inequality remains a pressing challenge. Despite sustained economic growth in the early 2000s, inequality has persisted. Although it began to decline in 2012, it remains among the highest in Southeast Asia. This paper examines how changes in education levels and occupational structure have influenced wage patterns over the past two decades, focusing on how the supply of skills and the composition of employment have shaped wage gaps. Using Labour Force Survey data from 2002 to 2024, the analysis reveals that the slow expansion in the supply of college-educated workers has maintained a high wage premium for skilled labour, thereby sustaining inequality. Returns to both college education and high-skill occupations are found to increase monotonically over the wage distribution, further contributing to the persistence of disparities. Changes in occupational structure have also influenced income distribution. Between 2002 and 2012, low- and middle-skilled jobs experienced relative wage gains. Between 2012 and 2016, middle-skilled occupations saw the fastest growth, contributing to a narrowing of wage inequality. Employment trends mirrored this pattern, with middle-skilled job growth peaking between 2012 and 2016. More recent trends point to a decline in middle-skilled employment; however, it remains unclear whether this shift reflects structural transformations in the labour market or is driven by temporary disruptions.

Keywords: Wage Inequality, Skills, Occupational Choice, Polarisation, RIF-Regressions.
JEL Classification: J31, J24, C31

Introduction

Over the past three decades, the Philippines has made substantial progress in reducing poverty, driven by sustained economic growth, structural transformation, and expansion of education. The national poverty rate declined from 49.2 per cent in 1985 to 16.7 per cent in 2018, reflecting the synergies between economic growth and social development. The COVID-19 pandemic temporarily reversed these gains, increasing poverty to 18.1 per cent by 2021, before it declined again to 15.5 per cent in 2023. Between 1985 and 2023, gross domestic product (GDP) expanded

[1]*The World Bank Group - Poverty and Equity Global Practice, United States of America.*
Corresponding Author Email: nbelghith@worldbank.org
[2]*The World Bank Group - Poverty and Equity Global Practice, United States of America.*
[3]*The World Bank Group - Poverty and Equity Global Practice, United States of America*

Note:
The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

at an average annual rate of 4.1 per cent (2.1 per cent per capita), despite periods of economic volatility. The pre-pandemic years experienced particularly robust growth, while the 2020 recession reduced GDP per capita by 10.5 per cent. The economy rebounded with growth of around 5–7 per cent from 2021 to 2024, signalling a resilient recovery.

Structural transformation has accompanied this growth. Agriculture's share of employment and value-added has declined steadily, with labour shifting into services and, to a lesser extent, industry. Educational attainment also improved: the share of workers aged 25 and older with primary education or less fell from 55 per cent in the late 1980s to 25 per cent in 2024, while those with some college or higher rose from 20 to 30 per cent. Yet, only 20 per cent of the workforce had completed college by 2024, highlighting ongoing challenges in skill development and upward mobility.

Income inequality has remained a persistent challenge. During the 1997–1998 Asian financial crisis, the Gini coefficient reached 47.5 per cent and remained elevated in the early 2000s. Since 2012, however, inequality has steadily declined, driven by pro-poor growth and labour transitions from agriculture to wage and nonfarm employment, particularly among lower-income households. By 2023, the Gini had narrowed to 39.3 per cent, yet inequality remains among the highest in Southeast Asia. The bottom 50 per cent of the population held only 23 per cent of the national income, while the top 10 per cent captured 33 per cent, with per capita income in the top decile approximately six times higher than in the bottom decile.

Decomposition analyses indicate that education gaps remain the most significant contributor to inequality, accounting for approximately 30 per cent of the Gini in 2023, followed by occupational disparities at 20 per cent, down from 32 per cent in the early 2000s. Wage income consistently contributes nearly 50 per cent of overall inequality, with the wage Gini coefficient stabilizing at 40 to 41 per cent from 2002 to 2012 before declining to 32 per cent by 2024.

This paper examines how changes in education and occupational structure have shaped wage distribution in the Philippines from 2002 to 2024. It examines the impact of skill supply, employment structure, and returns to education on wage gaps, offering insights into how labour market developments have influenced inequality.

A large body of literature analyses the impact of education and occupational shifts on wage inequality. In the United States, Autor et al. (2003) documented structural labour market changes characterized by growth in both high- and low-skilled occupations, as well as a decline in middle-skilled routine jobs—a pattern commonly referred to as job polarisation. Acemoglu and Autor (2011), Autor and Dorn (2013), and Autor (2019) build on several papers[4] by constructing task-based models classifying occupations into high-skill, middle-skill routine, middle-skill nonroutine, and low-skill, showing that technological advances and offshoring drove increasing inequality and a rising college wage premium despite the increasing supply of college-educated workers. Bárány and Siegel (2018) find that polarisation began even before widespread ICT adoption, with mechanization and sectoral shifts affecting occupational wage patterns. Autor et al. (2020) further highlight a "race between education and technology," where rising demand for skills competes with the supply of college graduates, explaining historical wage premia variation. Firpo et al. (2018) employ reweighted recentered influence function (RIF) regressions and how unions, occupations, and education influenced U.S. wage distribution across quantiles from the 1980s to 2010s.

---

[4]*These include several foundational papers classifying occupations such as Autor et al. (2003) and Acemoglu and Zilibotti (2001).*

Similar trends are observed in other high-income countries, including the UK, Germany, Norway, and Denmark (Goos et al., 2009; Spitz-Oener, 2006; Michaels et al., 2014; Autor, 2019). Han et al. (2023) demonstrate that South Korea's college wage premium increased despite rising tertiary attainment, primarily driven by technological change and shifts in trade toward skill-intensive industries. In Latin America, Acosta et al. (2019) report diverging trajectories for wage premia: tertiary education returns rose in the 1990s, declined sharply in the 2000s, and fell more gradually in the 2010s, whereas secondary education returns steadily declined, highlighting labour demand as a key determinant of wage premia. Caner et al. (2022) similarly find in Turkey that expanded university enrollment reduced the wage premium among younger graduates, illustrating supply-demand effects on education returns.

Evidence from developing countries remains more limited. Building on Autor (2014), an extensive cross-country comparison of occupational patterns from 1995 to 2012 reveals increasing employment polarization in several low- and middle-income countries, including Guatemala, Panama, and Turkey (World Bank, 2016). In these countries, the share of workers in high-skilled and low-skilled occupations has increased, while employment in middle-skilled occupations has decreased. However, the same analysis reveals a different trend emerging in countries such as Ethiopia and Nicaragua, where an expansion in middle-skilled occupations has accompanied the growth in high-skilled employment. Gochoco-Bautista et al. (2013) report modest declines in income polarization in the Philippines, with skill-related wage premiums contributing to increased inequality from the mid-1990s to the mid-2000s.

Except for Gochoco-Bautista et al. (2013), recent literature on inequality in the Philippines has primarily examined factors such as low levels of human capital, economic changes, and remittances—either as drivers of inequality or as forces that sustain it. Tuano and Cruz (2019) link persistent inequality to spatial employment disparities, SME constraints, and a "hollowed-out" industrial sector, as the economy transitioned from industry to low-productivity services, limiting social mobility. Balisacan (2019) and Balisacan and Fuwa (2004) note that sectoral composition, human capital, and infrastructure access drive income variation. Pernia (2008) finds international remittances reduce poverty but widen inequality, while domestic remittances are more equitable.[5] World Bank (2022) provides a comprehensive analysis of inequality in the Philippines, examining drivers such as inequality of opportunity, regional disparities, and the interplay between skill supply and employment structure. The report finds that while both international and domestic transfers have significantly reduced poverty, their effects on inequality differ: international remittances widen income gaps, whereas domestic remittances help mitigate them.

Despite a rich body of literature on inequality in the Philippines, the relationship between education, employment structure, and wage inequality remains underexplored. This paper addresses this gap by leveraging harmonised individual- and household-level survey data spanning two decades from 2002 to 2024, constructing a unique occupational crosswalk to track occupational trends over time and expanding the initial analytical work of Belhaj Hassine, Fernandez and Jandoc (2022). Drawing upon the frameworks of Acemoglu and Autor (2011), Autor (2019), and Bárány and Siegel (2018), and integrating Firpo et al.'s (2018) RIF approach, this study extends existing research by analyzing education and occupational shifts, and wage premia within the context of the Philippine labour market.

---

[5] *Pernia (2008) notes that remittances improve household investment in education and capital formation among poorer households. This may mitigate inequality in the long term assuming that educational attainment of children in higher income households is less influenced by remittances than in lower income households.*

The remainder of the paper is structured as follows: Section 2 describes the data and methodology used to assess structural labour market changes and their implications for income inequality. Section 3 presents the empirical findings, focusing on changes in occupational structure, skill distribution and wage disparities. Section 4 concludes with a discussion of key insights and policy implications.

Data and Methodology

The analysis primarily relies on data from the Labor Force Survey (LFS) covering the period from 2002 to 2024 and is complemented by information from recent rounds of the Family Income and Expenditure Survey (FIES), both produced by the Philippine Statistics Authority. The Philippines LFS, first conducted in 1956, is a quarterly nationwide survey conducted in January, April, July and October of each year, with each round typically covering at least 40,000 households.[6]

Designed to collect reliable and accurate statistics on both the levels and trends of labour and employment, the survey provides a framework for formulating labour market policies. It gathers data on employment, unemployment, and underemployment, as well as demographic and socioeconomic characteristics of the population. Despite its long history, the LFS only began publishing wage data from 2002 onwards. The FIES, on the other hand, is designed to be the primary source of family income and expenditure data in the Philippines. Collected once every three years, and then every two years starting in 2021, the survey is divided into two interview windows and serves as a rider survey to the July and January rounds of the LFS. The first visit, in July, covers income and expenditure data from January to June of the same year, while the second visit, in January, covers data from July to December of the previous year. The FIES provides data for some of the country's most important statistics for development, with the data used in measurements of poverty and the Human Development Index (HDI), as benchmark information for weights used in the estimation of the Consumer Price Index (CPI), as well as in estimating the country's poverty incidence and threshold (PSA, 2021).

The Philippines utilises the Philippine Standard Occupational Classification (PSOC) to categorise the occupations of its workers. Since 2001, the LFS has used two versions of PSOC to adapt to the changing nature of work and to align with international standards: the 1992 PSOC, used in LFS surveys from January 2001 to January 2016, was patterned after the International Standard Classification of Occupations 1988 (ISCO-88), while the 2012 PSOC, adopted from April 2016 and still currently in use, is based on ISCO 2008 (ISCO-08). As the period of analysis in this study encompasses both PSOC versions, the occupation codes needed to be harmonised to create continuity across rounds. An occupation crosswalk was constructed, harmonising the two-digit occupation codes used across LFS rounds to create 22 unique occupation codes that are as consistent as possible across time, given available data. The occupation codes were then grouped into broader occupation categories, where High-skill occupations comprise managers and managing proprietors, professionals, and associate professionals and technicians; Middle-skill routine occupations include clerical support workers, craft and related trades workers, sales workers, and plant and machine operators and assemblers; middle-skill nonroutine occupations include service workers, while low-skill occupations encompass elementary occupations, such as cleaners and helpers; and labourers in mining, construction, manufacturing and transport. While

---

[6]In 2021, the PSA began collecting the monthly LFS, a shortened version of the quarterly LFS, to better assess the impacts of the COVID-19 pandemic on labour and employment. This paper draws on LFS October quarterly data for the period 2002–2023, and on LFS January quarterly data for 2024, given that the October 2024 release is not yet available.

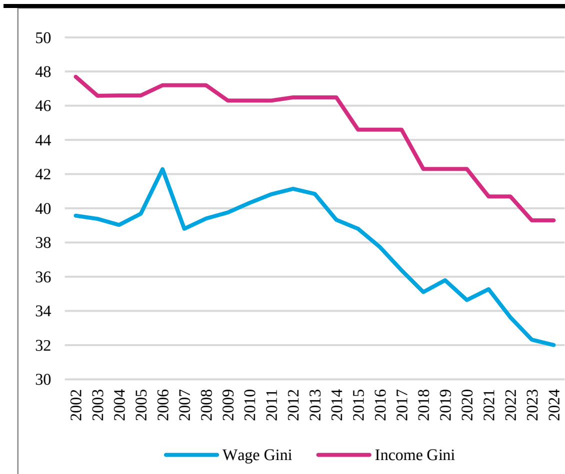
the process of creating balanced occupation codes broadly follows the occupational classification of Dorn (2009), Acemoglu and Autor (2011), and Bárány and Siegel (2018), the harmonisation used in this paper was adjusted to better suit the country's context.

We focus the analysis on a sample of employed wage workers aged 15 and above. As such, the analysis excludes the following categories of workers which the PSA classifies as non-wage workers: 1) self-employed without any paid employee, 2) employer in own family-operated farm or business, and 3) worked with or without pay in own family-operated farm or business.[7] Following Bárány and Siegel (2018), workers with missing wage data and those in armed forces occupations were excluded from the analysis.

By focusing on employed wage workers, the analysis identifies key trends in income and wage inequality and examines the roles of labour supply, educational attainment, skill valuation, skill availability and occupational composition in shaping the earnings distribution over time. Broadly, income and wage inequality in the Philippines have followed similar trends over the past two decades, which can be divided into two distinct phases.

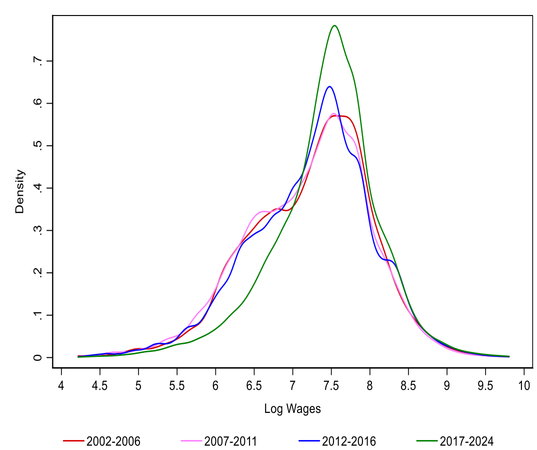
The first phase (2002–2012) was characterized by rising inequality, with both wage and income Gini coefficients increasing. This period followed the aftermath of the 1997–1998 Asian financial crisis, during which inequality surged and remained elevated despite rapid economic growth. The second phase, beginning in 2012, marked a reversal of this trend, with inequality entering a steady decline that accelerated in recent years (Figure 1). The density of log wages in Figure 2 further supports this shift, showing a more compressed wage distribution in the later years, indicating reduced wage dispersion.

Figure 1: Income and Wage Inequality trends 2002-2024



Source: Labor Force Survey (LFS) 2002–24 and FIES 2000-2023.[8]

Figure 2: Density of Log Wages 2002- 2024



Source: LFS 2002–2024.

One way to understand the patterns of earnings distribution over time is to begin by analyzing changes in labour supply, educational attainment, and wage earnings, and then delve deeper into

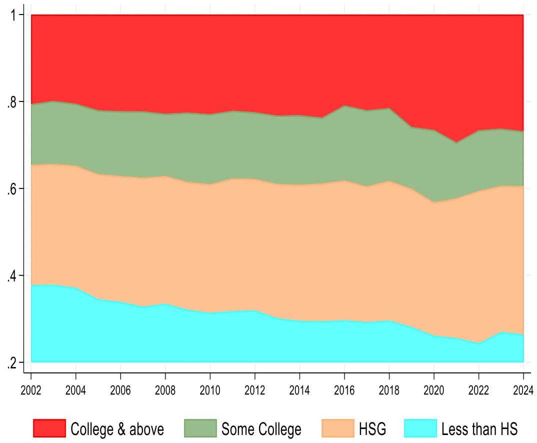
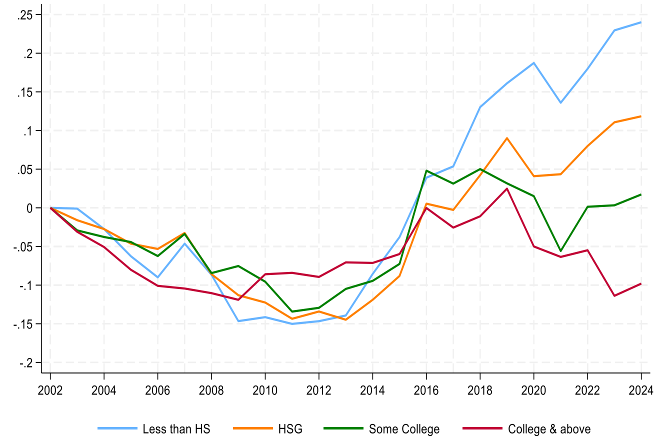
[7] *As mentioned, the LFS only began publishing wage data beginning in 2002, which limits the analysis to cover only the two decades from 2002-2024.*

[8] *Since income Gini data from FIES is available only every three years (and every two years since 2021), we assumed constant values between survey years.*

the valuation of skills, skills supply, and occupational composition. The Philippine labour market has undergone significant transformations over the past two decades, characterized by an expansion of wage employment and rising educational attainment. Between 2002 and 2024, the share of workers engaged in wage employment increased from 48 per cent to 68 per cent, with growth observed among both men and women. Male wage employment rose from 49 per cent to 70 per cent, while female wage employment increased from 47 per cent to 64 per cent. However, overall employment rates remain lower for women, at 47 per cent in 2024 compared to 70 per cent for men. The composition of the labour force has also shifted toward higher educational attainment. The share of hours supplied in wage employment by workers with less than a high school education declined from 38 per cent to 26 per cent, while the share of hours supplied by workers with a college degree or higher increased from 21 per cent to 27 per cent (Figure 3).[9] The rise in educational attainment has been particularly pronounced among women. By 2024, 40 per cent of female hours in wage employment were supplied by college-educated workers, compared to 19 per cent of male hours—up from 31 per cent and 14 per cent, respectively, in 2002 (Figure 1A in the appendix).

Real wage trends have evolved unevenly across education groups over the past two decades. Between 2002 and the early 2010s, real wages declined for all workers, remaining below their 2002 levels until 2016 (Figure 4). The decline was more pronounced among non-college-educated workers, whose real wages fell by around 15 per cent between 2002 and 2012, compared to a 10 per cent decline for those with some college or higher education. From 2012 onward, real wages began to recover, with non-college-educated workers experiencing faster growth—about 32 per cent between 2012 and 2024—compared to just 5 per cent for college-educated workers, contributing to narrowing wage inequality. The fastest wage increase for non-college-educated workers occurred between 2012 and 2016 (16 per cent), partly driven by transitions from low-skill to medium-skill occupations. Since 2016, wage growth has decelerated, marked by greater volatility and employment fluctuations across skill levels. Despite these shifts, substantial wage disparities persist. By 2024, the real wages of non-college-educated workers were 18 per cent higher than in 2002, while earnings for workers with some college or higher education saw no improvement. Nonetheless, the average real wage of workers with some college or higher remained nearly twice as high as that of non-college-educated workers in 2024.

[9] *The hours shares are estimated following Autor (2019) approach and reflect an equilibrium outcome shaped by labour market dynamics, not latent labour supply.*

Figure 3: Share of Hours Worked by Education Group	**Figure 4: Composition-Adjusted Real Log Weekly Wages**
	
Source: LFS 2002–2024.	*Source*: LFS 2002–2024.

The observed trends in labour supply and wage earnings highlight broader structural shifts in the labour market, which need to be analyzed in conjunction with the evolving valuation of skills, as reflected in the college wage premium, the relative supply of skilled labour, and occupational changes. The next section will explore these dynamics, focusing on the factors contributing to the persistence of a high college wage premium, its relationship to changes in the relative supply of skills, and how shifts in occupational composition are influencing wage trends across different education or skill groups. This analysis will provide deeper insights into the forces shaping earnings inequality and labour market outcomes.

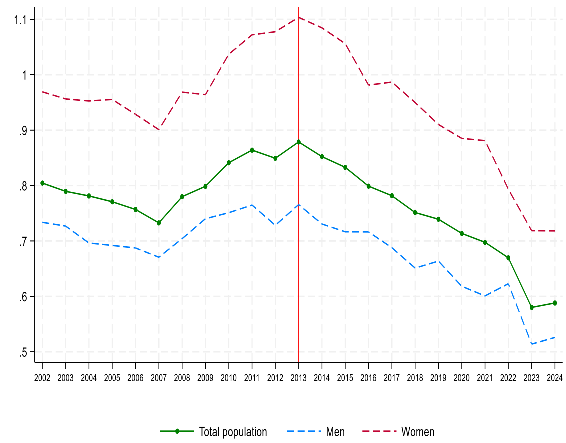
Skill Premium, Skill Supply, and Occupational Shifts

A useful starting point for understanding the pattern of wage inequality is to analyze trends in the college wage premium—the wage gap between college graduates and high school graduates, which can serve as a proxy for the market's valuation of skills.[10] As shown in Figure 5, the college wage premium has remained persistently high, though it has fluctuated over time. It declined during 2002–2007, rose sharply to a peak of 88 percentage points in 2013, and then steadily fell to 59 points by 2024. In that year, the average college graduate earned 80 per cent more than the average high school graduate, while workers with some college education earned 53 per cent more. Although the college premium has followed similar trends for both men and women, it has been consistently higher for women, indicating that disparities in returns to skills may be a more significant driver of inequality among women than among men. The trends in the college wage premium closely mirror broader patterns in wage inequality, suggesting that it plays an important role in sustaining inequality over time. The college wage premium is influenced by several factors, including the relative supply of skilled workers. Figure 6 suggests that the slow growth in the supply of college-educated workers, coupled with a persistent skills shortage, has maintained the

[10] *We estimate the college premium following Acemoglu and Autor (2011) by regressing log weekly wages for full-time workers annually on education dummies, experience, and gender. Composition-adjusted mean log wages are calculated at specific experience and education levels, weighted by average employment shares. The yearly ratio of mean log wages for college graduates to high school graduates is plotted over time.*

scarcity value of skills. This has kept the skill premium high and hindered faster progress in reducing wage inequality.

Figure 5: Composition-Adjusted College/ High-School Log Wage Ratio, 2002–24



Source: LFS 2002–2024.

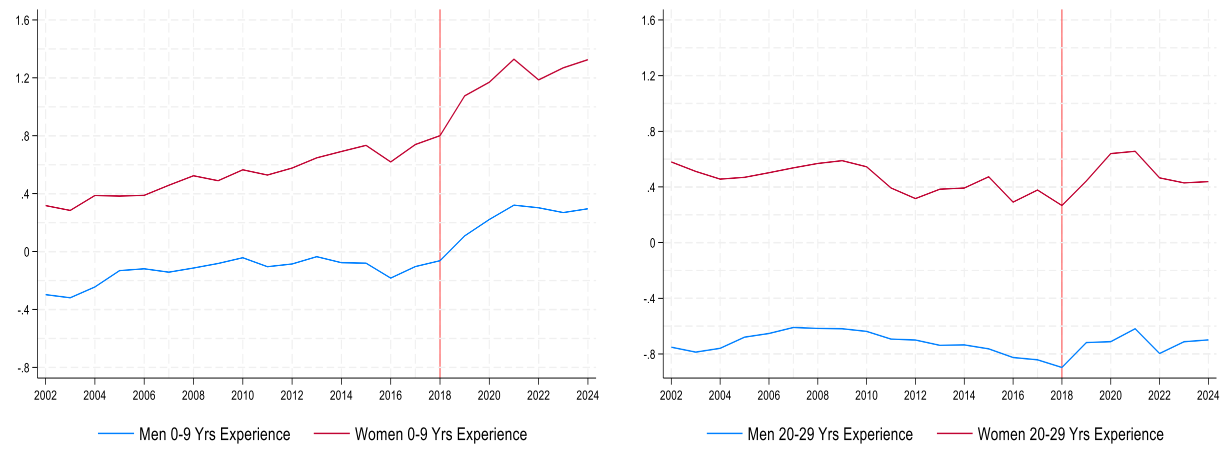
Figure 6: College/High-School Log Relative Supply, 2002–24

Source: LFS 2002–2024.

The supply of college-educated workers has seen only modest growth in recent years. Between 2002 and 2010, it increased marginally, followed by a slow decline from 2010 to 2018. However, it picked up again during 2018–2021 before declining slightly in 2024. The supply of college-educated workers has been consistently higher for women than for men, and it accelerated more rapidly for women during 2018–2021. This recent increase was driven primarily by young college graduates entering the labour market, with a particularly sharp rise in the relative supply of young women with college degrees (Figure 7.A). Figure 7.B further shows that the supply of experienced college graduates—those with 20–29 years of potential experience—grew only marginally, with most of the growth occurring among women. The gradual rise in tertiary education enrollment, especially among women, has contributed to a noticeable increase in the average education level of the labour force in recent years. However, despite these gains, the economy continues to face a significant skills shortage. This shortage not only constrains economic growth and productivity but also sustains a high skill premium, reinforcing persistent wage inequality.

Figure 7: College/High-School Log Relative Supply by Age, 2002–24

A. Young Cohort **B. Older Cohort**



Source: LFS 2002–2024. *Source*: LFS 2002–2024.

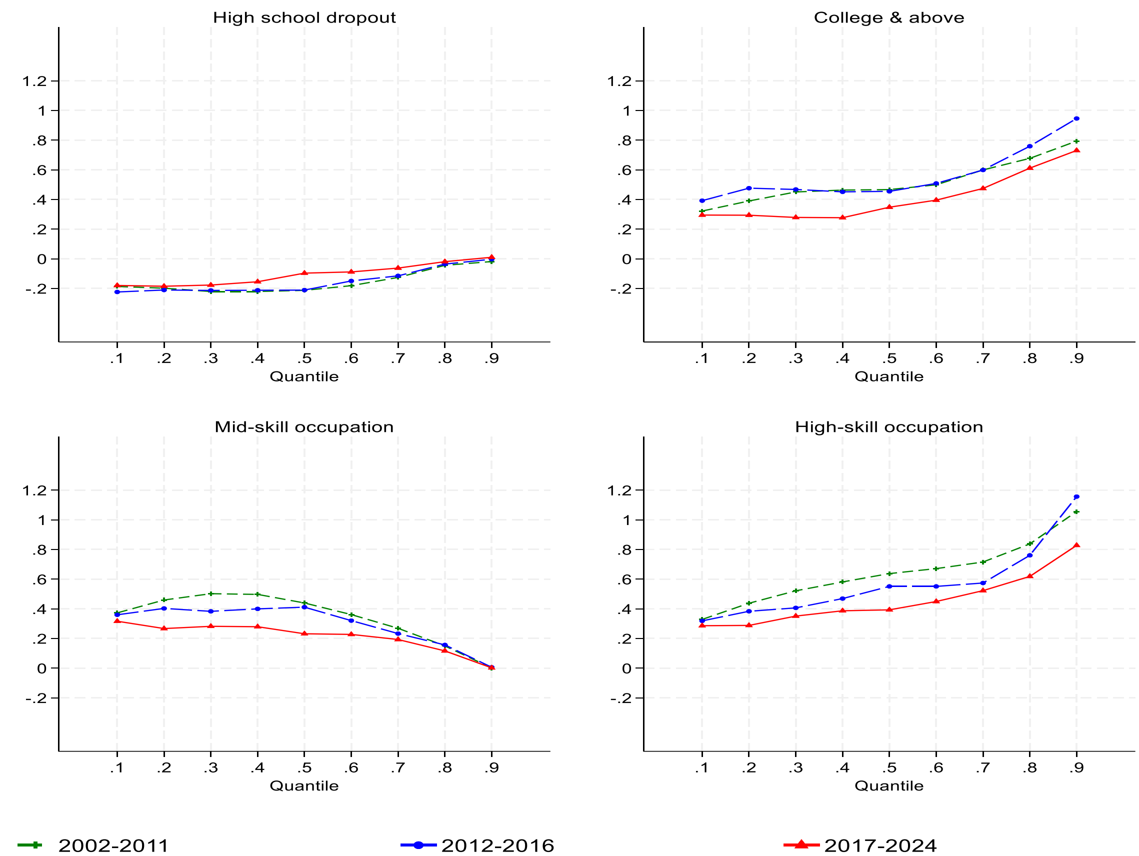
The college wage premium and skill supply may not fully capture important dimensions of inequality. Expanding the analysis to examine returns across the income distribution can offer a better understanding of how education and occupations contribute to inequality. These returns are estimated using Recentered Influence Function (RIF) regressions of unconditional quantiles of log real weekly wage income (Firpo et al. 2018), to examine how the rewards of education and skills vary across income groups. The analysis shows that increasing returns to college education and high-skill occupations across the income distribution play an important role in perpetuating wage inequality. As shown in Figure 8, returns to both college education and high-skill occupations rise monotonically with income percentiles, a pattern that has persisted over the past two decades, though with slight moderation in recent years (see also Figure 3A in the appendix). This indicates that higher-income individuals benefit disproportionately from higher education and high-skill jobs, further widening the wage gap. While the persistence of high returns to college education reflects the labour market's valuation of skills, the disparity in returns between high- and low-income groups is concerning. One explanation for this disparity is differences in school quality: individuals from lower-quality educational backgrounds tend to achieve lower labour market returns for the same level of education (Patrinos et al. 2006), exacerbating inequality.[11]

As shown by the RIF-regression coefficients for the 10th, 50th, and 90th quantiles and the wage income Gini coefficient in Tables 1A and 2A in the appendix, the inequality-enhancing effect of college education and high-skill employment is particularly pronounced at the top of the income distribution, where higher returns are concentrated. The inequality-enhancing effect of college education appears to be increasing over time, as evidenced by its positive impact on the wage Gini coefficient in Table 1A, while the impact of high-skill occupations remains relatively

[11] *A more general explanation lies in the complementary relationship between higher education and unobserved endowments, such as innate abilities, access to quality schooling, or social networks, which are more prevalent among higher-income groups (Buchinsky 1994; Mwabu and Schultz 1996). As a result, college education not only reinforces existing disparities but also amplifies them, as it complements rather than compensates for these unobservable advantages. The analysis of returns to education and occupations across household income groups reveals a more pronounced inequality-enhancing effect of college education and high-skill occupations (see World Bank 2022).*

unchanged. In contrast, secondary education and mid-skill occupations generally reduce inequality. While mid-skill jobs contribute to narrowing the wage gap, particularly at the higher end of the income distribution, they have a modest inequality-increasing effect at the lower end.

Figure 8: Returns to Education and Occupation by Quantile

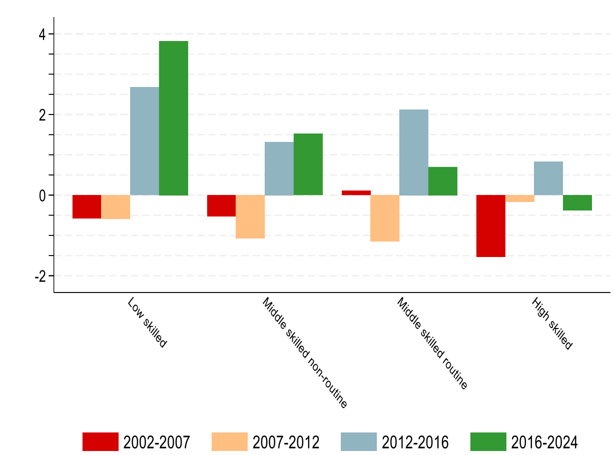


Source: LFS 2002–2024.

The 2010s were marked by a relative expansion of middle-skilled occupations and an increase in wages for low- and middle-earning groups, contributing to a moderation in wage inequality. Following Dorn (2009), Acemoglu and Autor (2011) and Bárány and Siegel (2018), we classify occupations into four broad categories—high-skill, middle-skill routine, middle-skill nonroutine, and low-skill— to examine changes in employment and wage trends. Between 2002 and 2012, real wages declined across all occupation groups, with the steepest drops occurring in middle- and high-skilled occupations (Figure 9). However, from 2012 onward, wages began to recover, with the most significant increases occurring for low- and middle-skilled workers. The period from 2012 to 2016 saw the highest wage growth for middle-skilled occupations, contributing to a decline in wage inequality. Employment trends mirrored this pattern, as middle-skilled occupations expanded significantly while the shares of low- and high-skilled employment declined (Figure 10). Beginning in 2002, employment in the Philippines was concentrated in middle- and low-skilled occupations, with 55 per cent of total hours in middle-skilled jobs (mainly routine) and 27 per cent in low-skilled jobs. Over the following two decades, high-skilled employment fell by about 1 percentage points, from 19 to 18 per cent of hours, while middle-skilled employment grew, peaking between 2012 and 2016 with a 3.6 percentage point increase. This shift was accompanied by a decline in low-skilled employment, which fell by 2.3 percentage points, from 26.8 to 24.5 per cent, reflecting a movement of workers into middle-skilled occupations. However, from 2016 to 2024, middle-skilled employment declined by 2.8 percentage points, driven primarily by a reduction in nonroutine middle-skill jobs. This decline was offset by rising employment in low-skilled occupations and, to a lesser extent, high-skilled occupations.

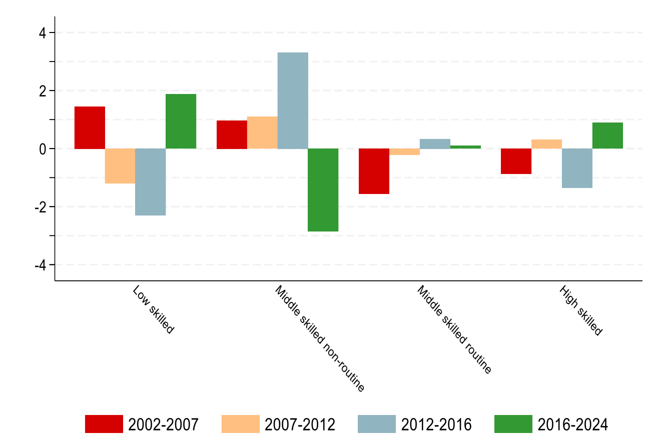
While the early 2010s suggested an upward shift, with more workers moving into middle-skilled jobs, recent trends indicate a movement of the middle-class toward lower-skilled employment, evidenced by the disproportionate growth in total hours worked in low-skilled occupations and a decline in middle-skilled occupations. This pattern raises concerns about the potential hollowing out of middle-tier jobs and the risk of economic polarization if the trend persists. While the decline in middle-skilled employment could reflect long-term technological shifts, as observed in advanced economies (Autor, 2019), it is unclear whether this trend is structural or driven by short-term cyclical factors, including the impact of COVID-19. This uncertainty underscores the need to monitor whether the earlier gains in reducing inequality were temporary and whether technological progress and digitalization are contributing to a longer-term polarization of the labour market. Nonetheless, the period since 2012—marked by relative wage gains for low- and middle-earning groups—has played an important role in reducing wage inequality, highlighting the importance of labour market dynamics in shaping income distribution.

Figure 9: Change in Log Wages by Occupation, 2002-2024, Per cent



Source: LFS 2002–2024.

Figure 10: Changes in Occupational Employment Shares, 2002-2024, Percentage Points

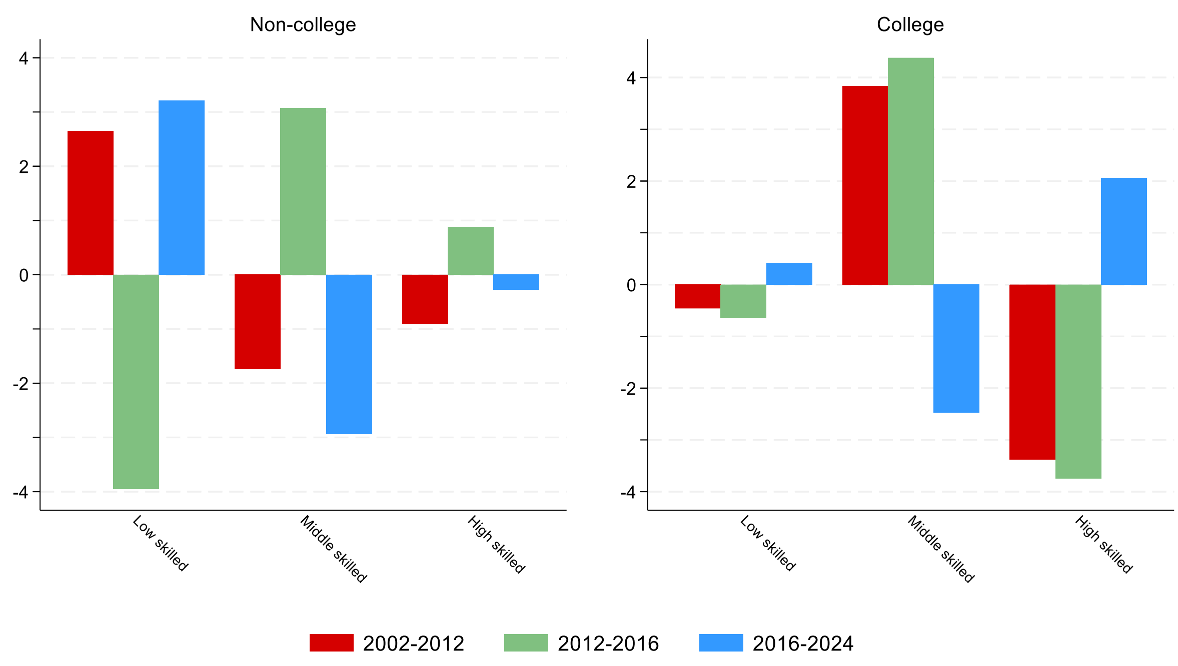


Source: LFS 2002–2024.

The analysis of occupational changes across education groups in Figure 11 provides a clearer picture of employment shifts across skill levels. Among college workers (those with some college or higher education), occupational movement between 2002 and 2024 was modestly, though not uniformly, directed toward middle-skill occupations. Over this period, the share of hours worked by college workers in high-skill occupations declined by over 5 percentage points (from 43 per cent to 37 per cent), while the share in middle-skill occupations increased from 49 per cent to 55 per cent. The share in low-skill occupations remained relatively stable at less than 8 per cent. However, these shifts were not uniform over time. Most of the transitions from high-skill to middle-skill occupations occurred between 2002 and 2016, with an acceleration in 2012–2016. Since 2016, signs of polarization have emerged, with college workers reallocating from middle-skill occupations to high-skill and to a lesser extent low-skill jobs. Compared to 2016, college workers have seen a slight upward shift in their occupational distribution. By 2024, the share of hours worked in high-skill jobs was about 2 percentage points higher, while the share in middle-skill jobs was 2.5 percentage points lower.

Among non-college workers (those with high school or lower education), occupational movement between 2002 and 2024 trended downward, though modestly and non-uniformly. Over this period, the share of non-college workers in high-skill occupations declined from 3.2 per cent to 2.9 per cent, while the share in middle-skill occupations fell from 58 per cent to 57 per cent. Conversely, the share in low-skill occupations increased by almost 2 percentage points (from 38.5 per cent to 40.4 per cent). Between 2002 and 2012, there was a notable shift of non-college workers from middle-skill to low-skill occupations. However, this trend reversed during 2012–2016, as the share of non-college employment in low-skill occupations fell by almost 4 percentage points, offset by a 3 percentage point increase in middle-skill occupations (from 57 per cent to 60 per cent), while the share in high-skill occupations saw a slight rise (from 2.3 per cent to 3.2 per cent). From 2016 to 2024, the trends shifted again, with middle-skill employment declining by about 3 percentage points, and low-skill employment increasing by the same proportion.

Figure 11: Changes in Occupational Employment Shares by Education Groups, 2002-2024, Percentage Points



Source: LFS 2002–2024.

Recent trends suggest a potential shift toward occupational polarization, with non-college workers increasingly moving from middle-skill to low-skill jobs, while college workers are modestly transitioning from middle-skill to high-skill jobs. These changes may be linked to ongoing technological and digital advancements, which tend to complement the skills of more educated workers. While technology tends to transform the nature of work for all, its effects can be more pronounced for less-educated workers, who experience a decline in opportunities for specialized, higher-paying middle-skill jobs. The pandemic may have accelerated these trends, with increased digitization, though the full extent of these changes remains to be seen as they require a longer time span for robust analysis.

The shift of non-college-educated workers toward middle-skill and, to a lesser extent, high-skill occupations between 2012 and 2016 likely contributed to faster real wage growth and a reduction in wage inequality. However, from 2016 to 2024, these gains partially reversed, as middle-skill employment declined and less-educated workers increasingly moved into low-skill jobs, signaling early signs of occupational polarization. Despite this shift, real wages for low-skill and less-educated workers continued to rise, potentially supported by incremental minimum wage increases, helping maintain the downward trend in wage inequality.[12] While these trends have not yet negatively impacted wage inequality, the persistence of polarization could pose longer-term risks, potentially widening wage disparities and reversing recent progress in reducing inequality.

We further analyze the evolution of wages among college and non-college workers in high-, medium-, and low-skill occupations using the kernel density reweighting technique developed by DiNardo, Fortin, and Lemieux (1996), referred to as DFL. This approach helps address the following question: How would wages for college and non-college workers have changed between 2002 and 2024 if occupational composition had evolved as observed, but wage levels within each occupation had remained fixed at their 2002 levels?[13].

Following DFL,[14] we consider the observed wage distribution $f(w)$ in year $t0$ as the joint distribution of wages w and covariates x (such as education, occupation, gender, etc.), integrated over the domain of covariates Ωx in year $t0$:

$$f_{t0}(w) = \int_{\chi\in\Omega\chi} dF(w, x \mid t_{w,x} = t0)$$

Using iterated expectations, this expression can be reformulated as:

$$f_{w_{t0}}^{x_{t0}}(w) = \int f(w \mid x, tw = t0)dF(x \mid tx = t0)$$

$$f_{w_{t0}}^{x_{t1}}(w) = \int f(w \mid x, tw = t0)dF(x \mid tx = t1)$$
$$= \int f(w \mid x, tw = t0) * \psi_x(x)dF(x \mid tz = t0)$$

The function $\widehat{\psi_x} = [\Pr(tx = t1 \mid x) / \Pr(tx = t0 \mid x)] * [\Pr(tx = t0)/\Pr(tx = t1)]$, which reweights the distribution of covariates in period $t0$ to match those in $t1$ is estimated using with a logit model.

---

[12]*This period, specifically from 2012 to 2016, seems to coincide with a sustained increase in real minimum wage rates. This topic could be explored further, but is beyond the scope of this paper.*

[13]*To simplify the analysis and isolate the impact of changes in occupational composition on wage trends, we hold wages fixed at their 2002-2011 levels. This approach allows us to focus on the significant occupational shifts and wage changes that occurred during the 2012-2024 period.*

[14]*See also Autor (2019).*

Figure 12: Observed and Counterfactual Changes in Log Wages, 2002-2024

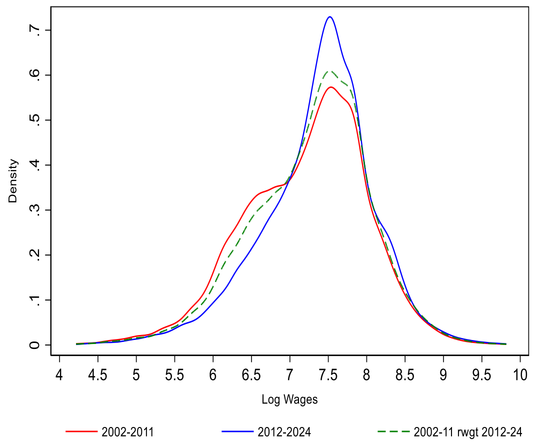
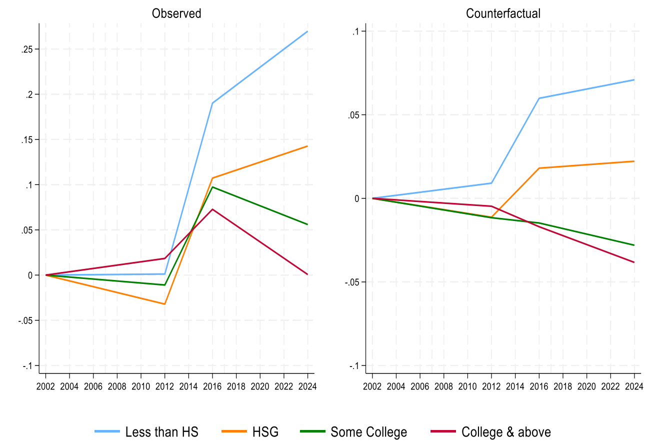
Observed and reweighted wage densities	Wage Changes by education group
	
Source: LFS 2002–2024.	*Source*: LFS 2002–2024.

Figure 12 presents the results of the reweighting analysis, which examines how changes in occupations and workforce characteristics have influenced wage distributions over time. Panel A compares the actual wage densities for 2002–2011 and 2012–2024 with a reweighted wage distribution (dashed green line). This counterfactual distribution simulates how the 2002–2011 wage distribution might have looked if the occupational structure had mirrored that of 2012–2024. The counterfactual wage distribution is more compressed than the actual 2002–2011 distribution, indicating that shifts in occupations and worker characteristics have contributed to reducing wage inequality. This suggests that occupational reallocation, particularly the movement of non-college workers into middle-skill jobs, have contributed to a more balanced wage structure over time.

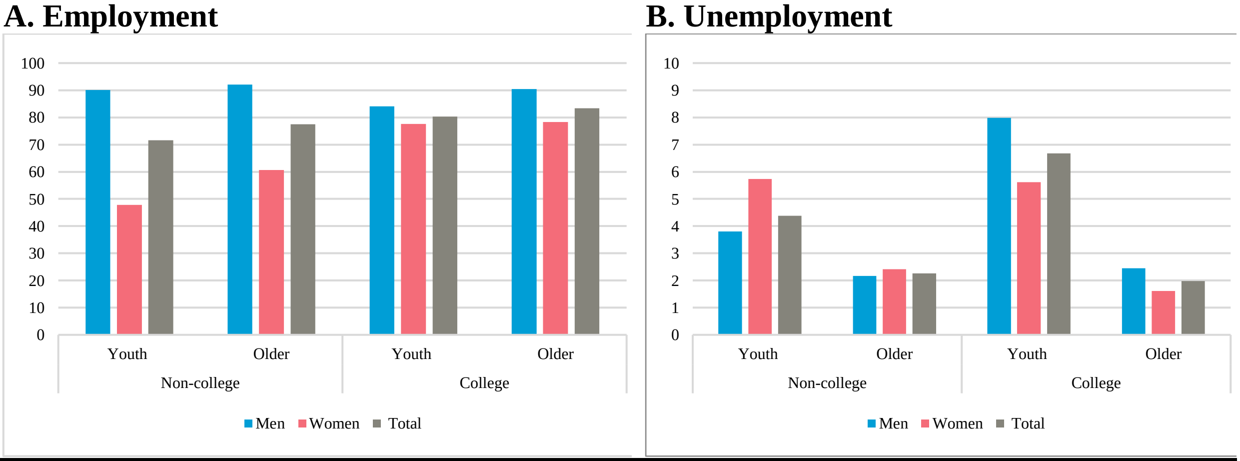
Panel B offers further insights into both the observed and counterfactual changes in wages by educational attainment over the past two decades. The left figure reports the observed pattern of wage earnings, revealing distinct trends across educational groups. For college-educated workers, real wages experienced a modest increase between 2002 and 2012, followed by a more pronounced rise from 2012 to 2016. However, this upward trend reversed after 2016, with real wages progressively declining through 2024. In contrast, workers with high school or lower education experienced a decline in real wages during the 2002-2012 period, but their wages rose steeply from 2012 to 2016 and continued to increase, albeit more modestly, in the subsequent years up to 2024. These patterns suggest a narrowing of wage inequality in recent years, driven by stronger wage growth for less-educated workers compared to college-educated workers.

The right graph (counterfactual) illustrates the effects of reweighting the 2002 wage distribution to reflect changes in occupational structure during the periods 2012–2016 and 2017–2024. Using the four broad occupation categories—low-, middle-, and high-skill occupations—for each of the four education groups as above, the analysis simulates how wage distributions would have evolved if occupational composition had shifted as observed, while holding wage levels within occupations fixed at their 2002–2011 levels. This approach isolates the impact of occupational reallocation on wage trends, providing insights into how changes in job composition have influenced wage outcomes across different education groups. It reveals that occupational reallocation account for a significant share of the rise in non-college wages after 2012, particularly during the 2012–2016 period. When examined by gender, the findings suggest that occupational changes were more influential for male non-college workers, as shifts in job structure disproportionately affected men (Figure 4A in the appendix). However, occupational reallocation does not seem to explain much of the wage trends for college-educated workers, as their wage changes are more likely driven by productivity variations, supply and demand dynamics, or other factors influencing wage levels within and between occupations.[15] Furthermore, the effect of occupational reweighting on college wages weakens after 2016, as occupational shifts among college workers were modest compared to those among non-college workers during this period.

Despite large college wage premiums, completing tertiary education does not automatically lead to better labour market outcomes, particularly for young graduates. In 2024, the unemployment rate among youth college graduates aged 25 to 34 stood at 6.7 per cent, significantly higher than the 4.4 per cent recorded for their peers with lower levels of education. While the gap is narrower among older graduates, they too experience higher unemployment rates relative to their peers particularly among men.[16] The elevated unemployment rates among younger entrants into the workforce could be due to higher reservation wages, which can prolong job searches and contribute to unemployment and absence from the labour market. Notably, 35 per cent of college graduates that were out of the labour force (excluding family reasons), were awaiting results of a job application compared to 9 per cent of non-college graduates. The high rate of unemployment among young graduates, which would likely be exacerbated by an increase in tertiary graduates, suggests that expanding tertiary education alone is not a panacea to reducing inequality.

Figure 13: Employment and Unemployment by Age, Education and Gender, 2024, Per cent

A. Employment **B. Unemployment**



Source: LFS 2024.

Note: Youth are aged 25 to 34 and older are aged 35 to 54; non-college educated are workers with high school degree or less and college educated are those who completed tertiary education.

---

[15]The DFL decomposition approach isolates the impact of occupational shifts by holding wage levels within occupations fixed, abstracting from broader economic forces that influence wage evolution over time. See also Autor (2019).

[16]The gender gap between male and female unemployment rate is likely due to social norms around employment in which men of working ages are almost all in labour force while women's participation is more dependent on household and individual characteristics including educational attainment. See Belhaj Hassine and Fernandez (2021) for more on female labour force participation.

Youth employment prospects also vary significantly by field of study, reflecting broader inequalities faced even by college-educated individuals—particularly as some fields offer more employment opportunities than others, shaping future prospects and reinforcing disparities. Graduates in disciplines such as natural sciences and mathematics appear to secure employment more easily. In contrast, some fields appear to place greater emphasis on experience or tenure. For instance, while young graduates with degrees in education experience higher unemployment rates compared to their peers, older graduates in the same field are almost universally employed.[17] However, in several of the most popular fields, unemployment remains persistently high. This is particularly evident in Information & Communication Technologies (ICT) and Engineering, Manufacturing & Construction—fields often perceived as highly valued and central to future economic growth. These trends suggest a skills mismatch, where students pursue fields they perceive as in demand, yet labour market conditions do not align with these expectations. Given this, a hypothetic policy increasing in the number of college graduates would need to account for the difference in labour market demand in varying fields of study.

Conclusion

The Philippines has made considerable progress in reducing poverty over the past three decades, driven by sustained economic growth, structural transformation and rising educational attainment. Despite this progress, inequality has been a persistent challenge. While income inequality has steadily declined since 2012, it remains among the highest in Southeast Asia.

This paper seeks to examine how changes in educational attainment and occupational structure have shaped wage distribution in the Philippines over the past two decades, focusing on how shifts in the relative supply of skills, changes in the structure of work and variations in returns to skills have influenced the reduction in wage inequality observed in more recent years. By analysing these dynamics, the paper aims to identify emerging labour market trends that may influence income inequality in the near future.

The analysis draws on data from the Philippine Labour Force Survey, spanning the years 2002 to 2024. To ensure comparability across survey rounds and account for changes in occupational classifications, an occupation crosswalk was constructed, and occupations were grouped into broad skill categories following Dorn (2009), Acemoglu and Autor (2011), and Bárány and Siegel (2018), allowing for a more nuanced assessment of wage and employment trends across occupation groups. The study first examines the wage premium and its relationship to the relative supply of skilled workers, with particular focus on trends in the supply of college-educated workers. Results indicate that although the college wage premium—the earnings gap between college and high school graduates—has fluctuated over time, it has remained persistently high, with the average college graduate earning approximately 80 per cent more than the average high school graduate in 2024. This persistence appears closely tied to the relatively slow growth in the supply of college-educated workers, suggesting that limited expansion of highly educated workers has sustained the skills premium and, in turn, contributed to persistent wage inequality.

To capture additional dimensions of inequality, the study uses RIF regressions of unconditional quantiles of log real weekly wage income to examine how returns to education and skills vary across the income distribution. The results show that over the past two decades, returns to both college education and high-skill occupations have increased monotonically across the wage distribution, indicating that higher-income workers disproportionately benefit from higher

[17] *Conditional on remaining in the labour force.*

education and high-skill occupations. This pattern underscores the labour market's strong valuation of skills while also highlighting persistent disparities in how the rewards of education and occupational skills are distributed across income groups, potentially reinforcing existing wage gaps.

Shifts in occupational structure have also played a significant role in shaping the income distribution. The wage trend from 2002 to 2012 reveals that middle- and low-skilled occupations experienced relative wage gains. The period from 2012 to 2016 marked the highest wage growth for middle-skilled occupations, which contributed significantly to the decline in wage inequality. Employment trends reflect this broad pattern, with the overall employment trend showing that middle-skilled occupations grew over the decade from 2002, reaching their peak during the 2012-2016 period. However, a different trend is emerging, with a shift away from middle-skilled occupations towards both high- and low-skilled occupations beginning in 2016.

An analysis of occupational changes across education groups provide a clearer picture of employment shifts across skill levels. Among higher-educated workers (those with at least some college education), the overall trend is directed towards middle-skilled occupations. Since 2016, however, there appears to be a shift away from middle-skilled occupations towards both high-skilled and low-skilled work. In contrast, occupational movement among non-college workers (those with at most a high school education) has broadly trended downwards, with the share in low-skilled occupations rising in recent years.

Recent trends suggest a decline in middle-skilled employment and a shift toward rising employment shares in high-skilled occupations (for college-educated workers) and low-skilled occupations (for non-college-educated workers). This divergence could be linked to ongoing technological and digital advancements, which disproportionately benefit more educated workers. While technology changes the nature of work for most workers, its effects are more pronounced for less educated workers, who may experience a decline in opportunities for higher-paying, middle-skilled jobs. It is currently unclear whether these emerging trends are structural or driven by short-term cyclical factors, including the impact of the COVID-19 pandemic. While the pandemic may have accelerated the trend toward digitalisation, the full extent of these changes remains to be seen, as they require a longer time span for robust analysis.

Policies may help mitigate significant disparities in income inequality, particularly in light of the changing nature of work. Enhancing foundational skills, such as math and literacy, at the basic education level can ensure that future workers can adapt to changing labour market demands. Closing the quality gap in higher education could also mitigate the trends identified in this paper, which show that higher-income individuals disproportionately benefit from higher education. Expanding skills development programs, particularly in digital technologies such as artificial intelligence, in close consultation with the private sector, could help workers transition to jobs that match the needs of the labour market. Increasing access to tertiary education could raise the productivity of the labour force, promote innovation, and potentially reduce wage inequality; however, it is essential to note that it is not a cure-all. For one, despite significant college wage premiums, young college graduates have unemployment rates that are significantly higher than those of their peers with lower levels of education. Furthermore, employment prospects among young people also appear to vary significantly depending on their field of study.

Interventions can also focus on policies that foster entrepreneurship, support job creation, and strengthen skills matching. Strengthening Active Labour Market Programs (ALMPs), which include job search assistance, career counselling, and training, could also support both new entrants and displaced workers in finding or transitioning to more productive jobs. This may be particularly valuable to address potential skill mismatches in the labour market. While beyond the scope of this paper, this topic could be worth exploring for future research. Subsequent studies could also explore how school quality influences labour market outcomes, as well as trends in the potential polarisation of jobs in the Philippines.

References

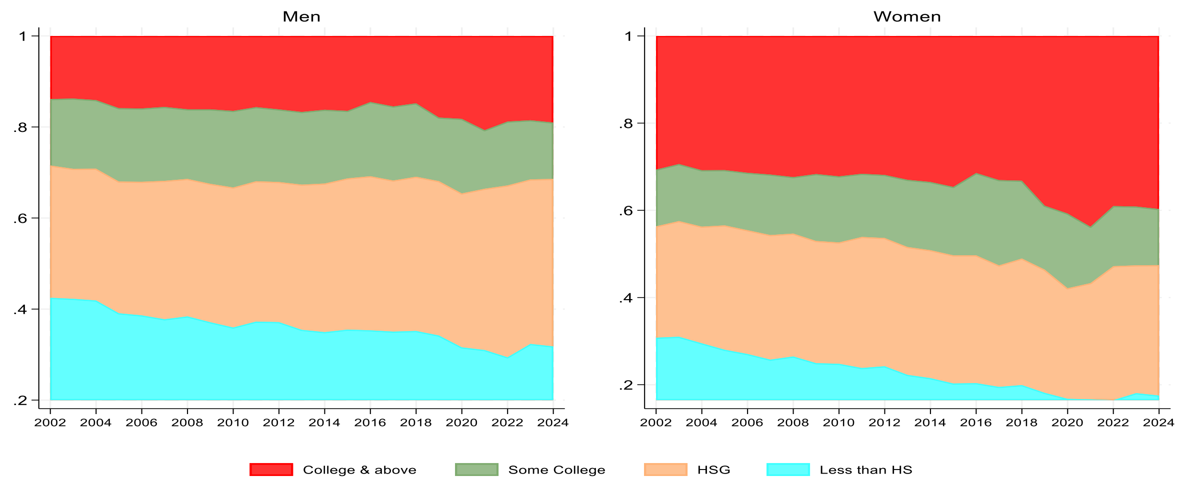
- Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 4, pp. 1043–1171). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5
- Acemoglu, D., & Zilibotti, F. (2001). Productivity differences. *The Quarterly Journal of Economics*, *116*(2), 563–606.
- Acosta, P., Cruces, G., Galiani, S., & Gasparini, L. (2019). Educational upgrading and returns to skills in Latin America: Evidence from a supply-demand framework. *Latin American Economic Review*, *28*(18). https://doi.org/10.1186/s40503-019-0076-2
- Autor, D. (2011). The polarization of job opportunities in the U.S. labor market: Implications for employment and earnings. *Brookings Institution.* https://www.brookings.edu/articles/the-polarization-of-job-opportunities-in-the-u-s-labor-market-implications-for-employment-and-earnings/
- Autor, D. (2014). *Polanyi's paradox and the shape of employment growth* (NBER Working Paper No. 20485). National Bureau of Economic Research. https://doi.org/10.3386/w20485
- Autor, D. (2019). Work of the past, work of the future. *AEA Papers and Proceedings*, *109*, 1–32. https://doi.org/10.1257/pandp.20191110
- Autor, D., Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, *103*(5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553
- Autor, D., Goldin, C., & Katz, L. (2020). Extending the race between education and technology. *AEA Papers and Proceedings*, *110*, 347–351. https://doi.org/10.1257/pandp.20201078
- Autor, D., Levy, F., & Murnane, R. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801
- Balisacan, A. (2019). Toward a fairer society: Inequality and competition policy in developing Asia. *Philippine Review of Economics*, *56*(1–2), 127–146.
- Balisacan, A., & Fuwa, N. (2004). Changes in spatial income inequality in the Philippines: An exploratory analysis. *Philippine Journal of Development*, *31*(2), 1–42.
- Bárány, Z. L., & Siegel, C. (2018). Job polarization and structural change. *American Economic Journal: Macroeconomics*, *10*(1), 57–89. https://doi.org/10.1257/mac.20150258
- Belhaj Hassine, N. B., & Fernandez, F. C. (2021). Women, childcare and social norms in the Philippines [Policy brief]. World Bank. https://documents1.worldbank.org/curated/en/099830003012240232/pdf/P1730020c322d10d30a7e500df58cd6f3bd.pdf
- Belhaj Hassine, N. B., Fernandez, F. C., & Jandoc, K. (2022). *Structural transformation, job polarization and inequality in the Philippines: A policy brief.* World Bank. http://documents.worldbank.org/curated/en/099702010182235861
- Buchinsky, M. (1994). Changes in the U.S. wage structure 1963–1987: Application of quantile regression. *Econometrica*, *62*(2), 405–458. https://doi.org/10.2307/2951618
- Caner, A., Demirel-Derebasoglu, M., & Oken, C. (2022). *Higher education expansion and college wage premium: Evidence from Turkey*. Bahçeşehir University, Betam.

https://betam.bahcesehir.edu.tr/wp-content/uploads/2022/09/Higher-Education-Expansion-and-College-Wage-Premium-Evidence-from-Turkey.pdf

- DiNardo, J., Fortin, N. M., & Lemieux, T. (1996). Labor market institutions and the distribution of wages, 1973–1992: A semiparametric approach. *Econometrica, 64*(5), 1001–1044. https://doi.org/10.2307/2171954
- Dorn, D. (2009). *Essays on inequality, spatial interaction, and the demand for skills* (Doctoral dissertation). University of St. Gallen. https://www.e-helvetica.nb.admin.ch/api/download/urn%3Anbn%3Ach%3Abel-152672%3Adis3613.pdf/dis3613.pdf
- Firpo, S. P., Fortin, N. M., & Lemieux, T. (2018). Decomposing wage distributions using recentered influence function regressions. *Econometrics*, *6*(2), Article 2. https://doi.org/10.3390/econometrics6020028
- Gochoco-Bautista, M. S., Bautista, C. C., Maligalig, D. S., & Sotocinal, N. R. (2013). Income polarization in Asia. *SSRN Electronic Journal*. https://papers.ssrn.com/abstract=2285849
- Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in Europe. *American Economic Review, 99*(2), 58–63. https://doi.org/10.1257/aer.99.2.58
- Han, J.-S., Lee, J.-W., & Song, E. (2023). Skill substitutability, trade with China and college wage premium in Korea. *The World Economy, 47*(2), 415–439. https://doi.org/10.1111/twec.13404
- Lemieux, T. (2006). Postsecondary education and increasing wage inequality. *American Economic Review, 96*(2), 195–199. https://doi.org/10.1257/aer.96.2.195
- Michaels, G., Natraj, A., & Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over 25 years (NBER Working Paper No. 16138). National Bureau of Economic Research. https://doi.org/10.3386/w16138
- Mwabu, G., & Schultz, T. P. (1996). Education returns across quantiles of the wage function: Alternative explanations for returns to education by race in South Africa. *American Economic Review, 86*(2), 335–339.
- Patrinos, H., Ridao-Cano, C., & Sakellariou, C. (2006). *Estimating the returns to education: Accounting for heterogeneity in ability* (Policy Research Working Paper No. 4040). World Bank. https://doi.org/10.1596/1813-9450-4040
- Pernia, E. M. (2008). *Migration remittances, poverty and inequality: The Philippines* (Discussion Paper No. 200801). University of the Philippines, School of Economics.
- Philippine Statistics Authority. (2021). *Technical notes—2021 family income and expenditure survey (Visit 1)*. https://psa.gov.ph
- Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, *24*(2), 235–270. https://doi.org/10.1086/499972
- Tuaño, P. A., & Cruz, J. (2019). Structural inequality in the Philippines: Oligarchy, (im)mobility and economic transformation. *Journal of Southeast Asian Economies*, *36*(3), 304–328. https://doi.org/10.1355/ae36-3c
- World Bank. (2016). *World development report 2016: Digital dividends.* World Bank. https://www.worldbank.org/en/publication/wdr2016
- World Bank. (2022). *Overcoming poverty and inequality in the Philippines: Past, present, and prospects for the future.* World Bank. http://documents.worldbank.org/curated/en/099325011232224571/P17486101e29310810abaf0e8e336aed85a

Appendix

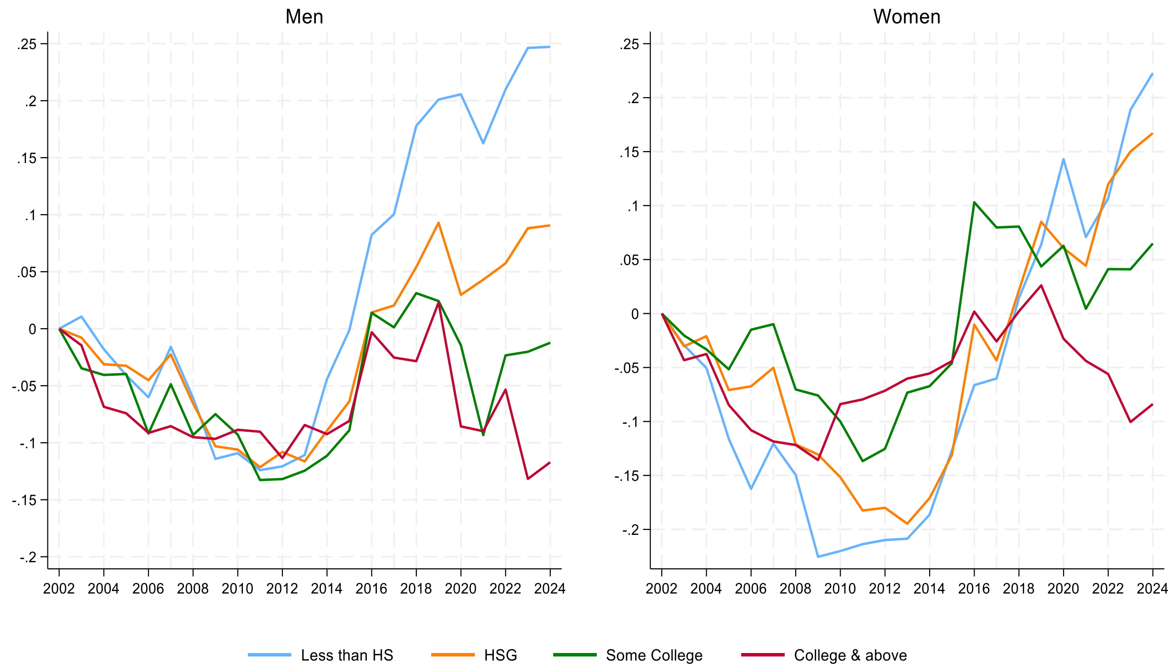
Figure 1A. Share of Hours Worked by Education Group and Gender, 2002-2024



Source: LFS 2002–2024.

Note: The sample consists of all wage-employed individuals aged 15 and older (work in nonfarm-nonmilitary).

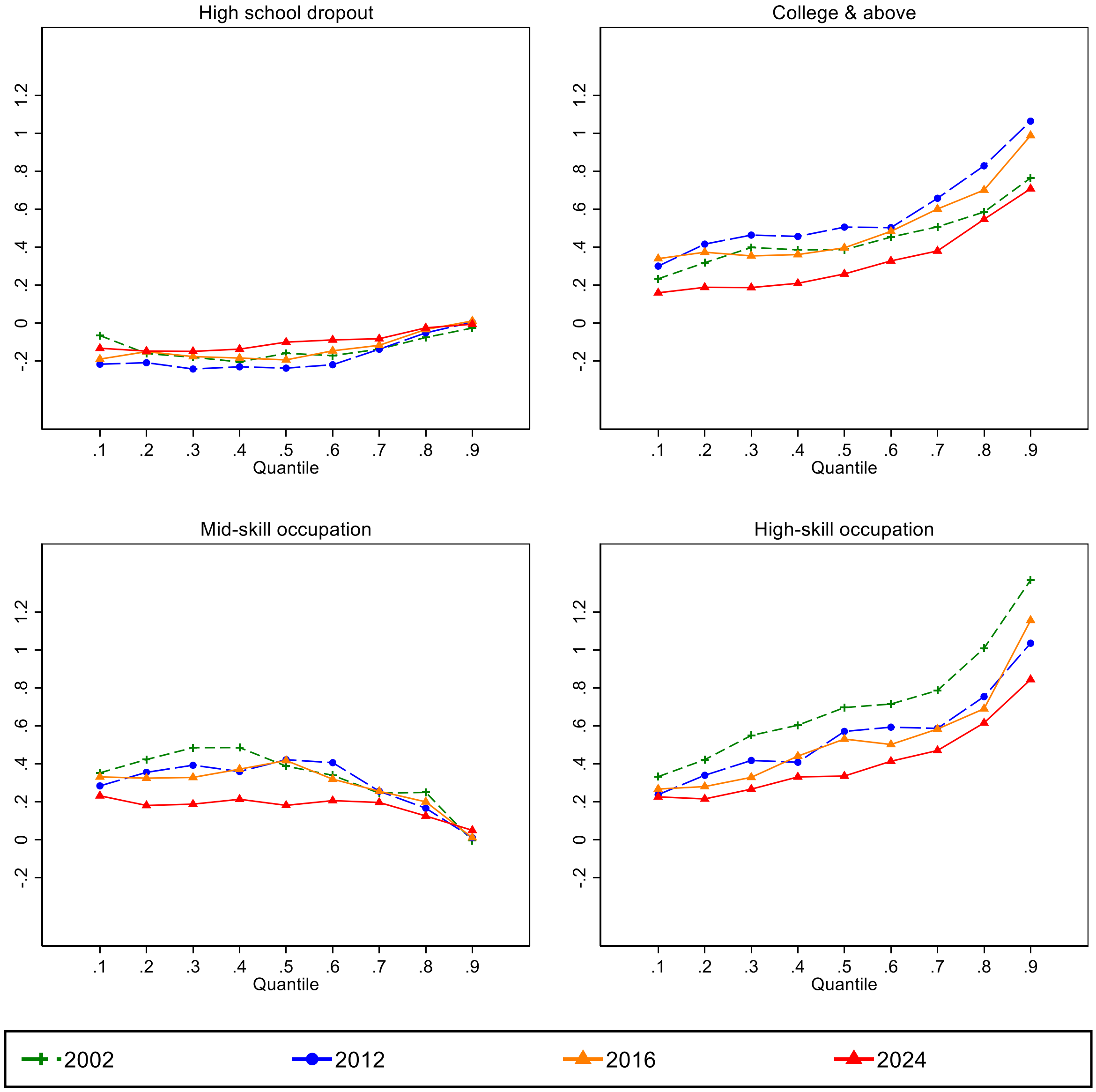
Figure 2A: Composition-Adjusted Real Log Weekly Wages by Education and Gender, 2002-2024



Source: LFS 2002–24.

Note: The figure illustrates cumulative changes in real log weekly wage earnings, following the methodology of Acemoglu and Autor (2011) and Autor (2019). The series represent composition-adjusted mean log wages for gender-education-experience groups, categorized into four education levels and five potential experience brackets (0–9, 10–19, 20–29, 30–39, and 40+ years). Log weekly wages are regressed annually by gender on education dummies, a quartic function of experience, and their interactions. The composition-adjusted mean log wage for each of the 40 groups is derived as the predicted log wage at specific experience and education levels. All values are adjusted for inflation using the consumer price index (CPI).

Figure 3A: Returns to Education and Occupation by Quantile for Selected Years



Source: LFS 2002–2024.

Table 1A: RIF Regression of Wage Gini

	2002/11	2012/16	2017/24
Less than Elementary	0.079***	0.074***	0.065***
	(0.004)	(0.003)	(0.002)
Elementary	0.037***	0.045***	0.040***
	(0.003)	(0.003)	(0.002)
Some High School	0.048***	0.053***	0.053***
	(0.003)	(0.003)	(0.002)
Some College	-0.026***	-0.029***	-0.008***
	(0.003)	(0.002)	(0.001)
College & above	0.056***	0.058***	0.079***
	(0.004)	(0.003)	(0.002)
Experience < 10 yrs	-0.033***	-0.039***	-0.040***
	(0.003)	(0.002)	(0.001)
Experience 10-20 yrs	-0.026***	-0.022***	-0.017***
	(0.003)	(0.002)	(0.001)
Experience 30-40 yrs	0.007	0.008**	0.019***
	(0.004)	(0.003)	(0.002)
Experience >= 40 yrs	0.013*	0.012**	0.039***
	(0.005)	(0.004)	(0.002)
High skilled	0.089***	0.086***	0.090***
	(0.004)	(0.003)	(0.002)
Middle skilled routine	-0.111***	-0.102***	-0.085***
	(0.003)	(0.002)	(0.001)
Middle skilled nonroutine	-0.047***	-0.043***	-0.013***
	(0.004)	(0.003)	(0.002)
Low-end services	-0.054***	-0.051***	-0.079***
	(0.003)	(0.003)	(0.002)
High-end services	-0.108***	-0.106***	-0.119***
	(0.004)	(0.004)	(0.002)
Manufacturing	-0.132***	-0.140***	-0.152***
	(0.004)	(0.003)	(0.002)
Public Sector	-0.034***	0.051***	0.055***
	(0.004)	(0.003)	(0.002)
Female	0.031***	0.047***	0.036***
	(0.002)	(0.002)	(0.001)
Constant	0.492***	0.473***	0.424***
	(0.004)	(0.003)	(0.002)
Observations	339,018	189,629	540,424
Adjusted R-squared	0.036	0.103	0.095

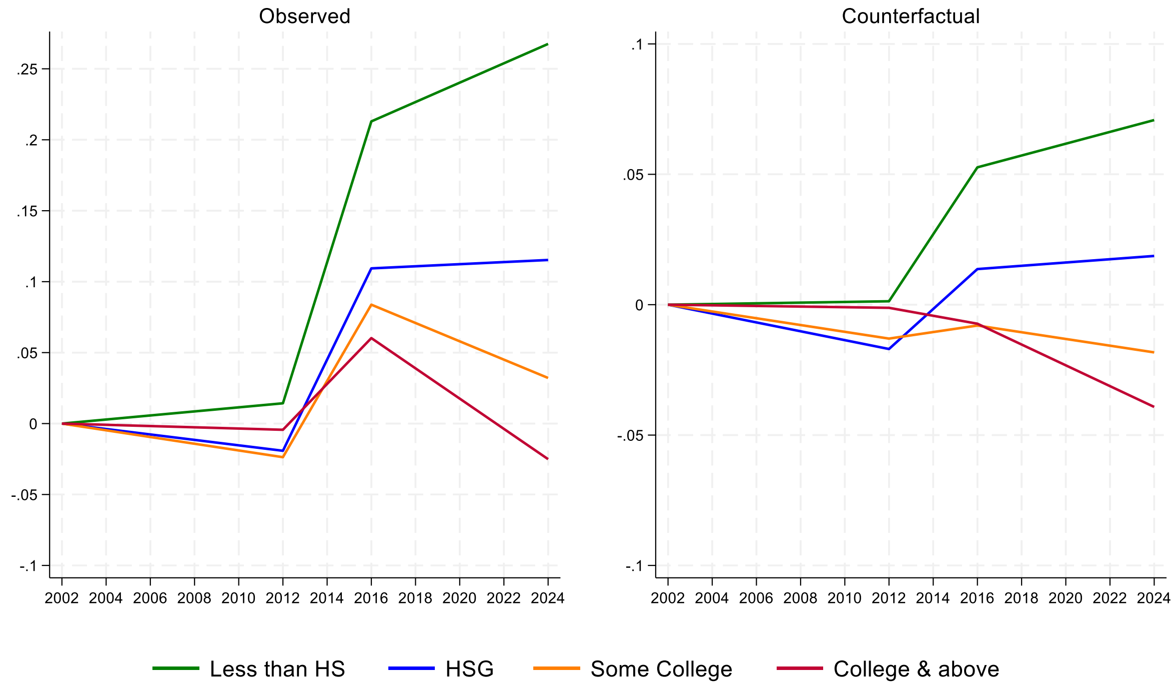
Source: LFS 2002–24.
Note: Bootstrapped standard errors, based on 100 repetitions, are reported in parentheses. Significance levels are denoted by: *** p ≤ 0.01, ** p ≤ 0.05, * p ≤ 0.1. The base group consists of individuals who are, not employed in the public sector, hold a high school degree, have 20-30 experience, work in construction, and are in low-skill occupations.

Table 2A: Unconditional Quantile Regression Coefficients on Log Wage

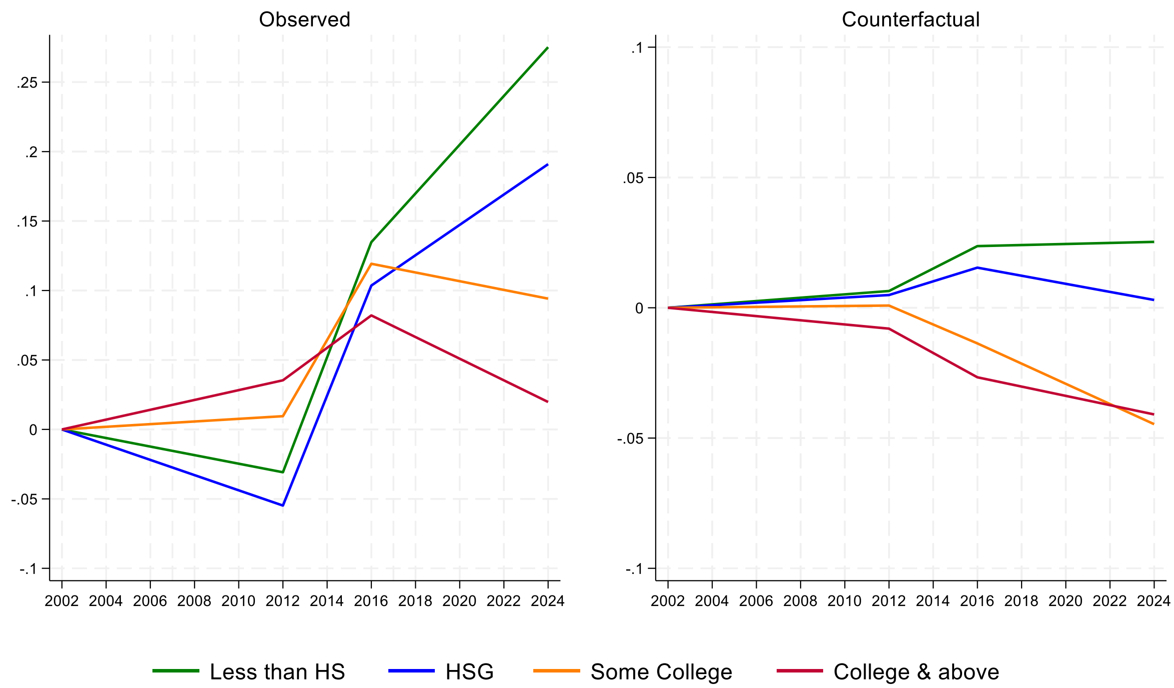
	2002/11			2012/16			2017/24		
	Q10	Q50	Q90	Q10	Q50	Q90	Q10	Q50	Q90
Below Elem.	-0.451***	-0.366***	-0.065***	-0.506***	-0.299***	-0.023*	-0.470***	-0.183***	-0.020***
	(0.008)	(0.005)	(0.006)	(0.012)	(0.006)	(0.010)	(0.008)	(0.003)	(0.005)
Elementary	-0.210***	-0.282***	-0.069***	-0.260***	-0.237***	-0.029**	-0.299***	-0.138***	-0.020***
	(0.007)	(0.005)	(0.006)	(0.012)	(0.006)	(0.009)	(0.008)	(0.003)	(0.005)
Some HS	-0.256***	-0.245***	-0.031***	-0.321***	-0.221***	-0.013	-0.342***	-0.128***	-0.003
	(0.007)	(0.005)	(0.006)	(0.011)	(0.006)	(0.009)	(0.007)	(0.003)	(0.004)
Some College	0.095***	0.232***	0.097***	0.130***	0.209***	0.086***	0.122***	0.104***	0.100***
	(0.007)	(0.005)	(0.005)	(0.010)	(0.005)	(0.008)	(0.007)	(0.002)	(0.004)
College & above	0.228***	0.525***	0.763***	0.302***	0.478***	0.877***	0.373***	0.298***	0.659***
	(0.008)	(0.005)	(0.006)	(0.012)	(0.006)	(0.009)	(0.007)	(0.002)	(0.004)
Exper < 10 yrs	-0.120***	-0.166***	-0.252***	-0.114***	-0.143***	-0.214***	-0.139***	-0.107***	-0.180***
	(0.006)	(0.004)	(0.005)	(0.009)	(0.005)	(0.007)	(0.006)	(0.002)	(0.004)
Exper 10-20	0.005	-0.018***	-0.104***	0.016	-0.016**	-0.026***	0.019**	-0.022***	-0.019***
	(0.006)	(0.004)	(0.005)	(0.010)	(0.005)	(0.008)	(0.006)	(0.002)	(0.004)
Exper 30-40	-0.015	0.002	0.036***	-0.008	-0.001	0.003	-0.050***	-0.007**	-0.008
	(0.008)	(0.005)	(0.006)	(0.012)	(0.006)	(0.009)	(0.007)	(0.003)	(0.004)
Exper >= 40	-0.146***	-0.059***	-0.078***	-0.200***	-0.071***	-0.095***	-0.337***	-0.064***	-0.064***
	(0.011)	(0.007)	(0.009)	(0.016)	(0.008)	(0.013)	(0.010)	(0.003)	(0.006)
High skilled	0.248***	0.687***	0.904***	0.319***	0.563***	1.003***	0.360***	0.391***	0.723***
	(0.009)	(0.006)	(0.007)	(0.013)	(0.007)	(0.010)	(0.008)	(0.003)	(0.005)
Middle skilled routine	0.296***	0.484***	0.006	0.373***	0.411***	0.012	0.451***	0.243***	0.010**
	(0.006)	(0.004)	(0.005)	(0.009)	(0.005)	(0.007)	(0.006)	(0.002)	(0.003)
Middle skilled nonroutine	0.168***	0.366***	0.160***	0.207***	0.294***	0.121***	0.218***	0.143***	0.127***
	(0.009)	(0.006)	(0.007)	(0.013)	(0.007)	(0.010)	(0.008)	(0.003)	(0.005)
Low-end services	0.407***	0.172***	0.017**	0.387***	0.139***	-0.043***	0.615***	0.143***	-0.032***
	(0.007)	(0.005)	(0.006)	(0.012)	(0.006)	(0.009)	(0.008)	(0.003)	(0.005)
High-end services	0.581***	0.486***	0.101***	0.599***	0.425***	0.084***	0.907***	0.363***	0.079***
	(0.009)	(0.006)	(0.008)	(0.015)	(0.007)	(0.012)	(0.010)	(0.003)	(0.006)
Manufacturing	0.621***	0.534***	0.026***	0.699***	0.479***	0.001	1.022***	0.336***	0.009
	(0.008)	(0.005)	(0.006)	(0.012)	(0.006)	(0.009)	(0.008)	(0.003)	(0.005)
Public Sector	-0.049***	-0.127***	0.052***	-0.072***	-0.154***	0.543***	-0.133***	-0.129***	0.312***
	(0.008)	(0.005)	(0.006)	(0.012)	(0.006)	(0.010)	(0.008)	(0.003)	(0.005)
Female	-0.287***	-0.217***	-0.103***	-0.364***	-0.203***	-0.040***	-0.439***	-0.139***	-0.069***
	(0.004)	(0.003)	(0.004)	(0.007)	(0.004)	(0.005)	(0.005)	(0.002)	(0.003)
Constant	5.771***	6.817***	7.934***	5.763***	6.896***	7.861***	5.774***	7.142***	7.932***
	(0.008)	(0.005)	(0.007)	(0.013)	(0.006)	(0.010)	(0.009)	(0.003)	(0.005)
Observations	339,019	339,019	339,019	189,629	189,629	189,629	540,424	540,424	540,424
Ad. R-squared	0.128	0.389	0.299	0.127	0.354	0.343	0.140	0.282	0.276

Figure 4A: Observed and Counterfactual Changes in Log Wages by Gender, 2002-2024

Men

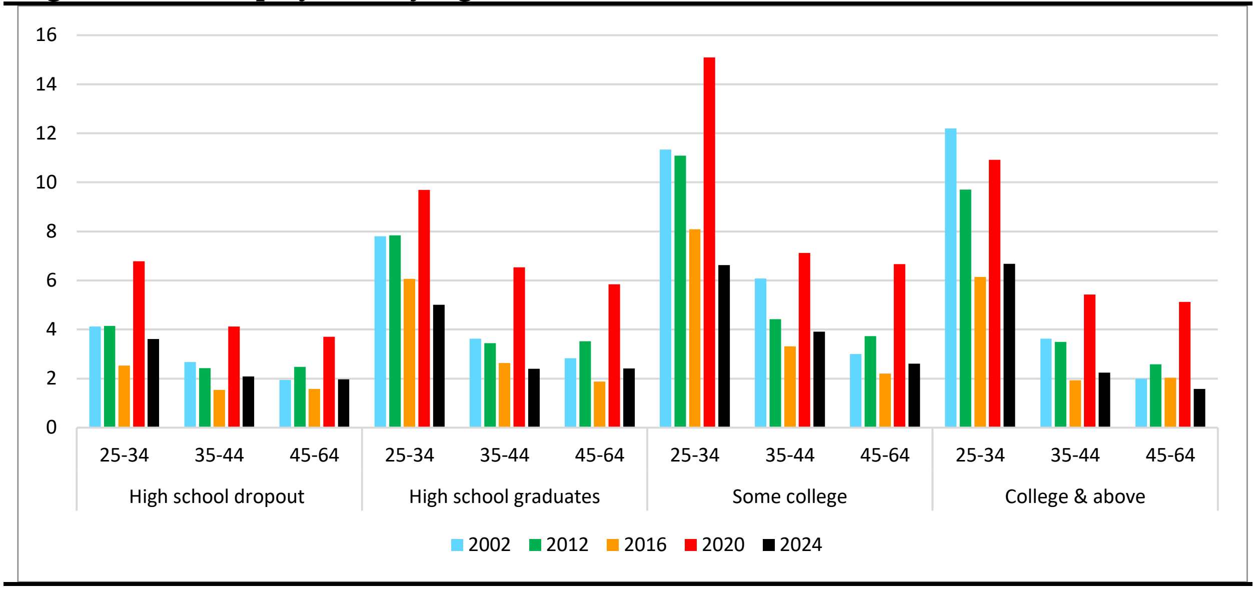


Women



Source: LFS 2002–2024.

Figure 5A: Unemployment by Age, and Education, 2002- 2024, Per cent



Source: LFS 2002, 2012, 2016, 2020, 2024.