Female Employment Transition: The Ripple Effects of Brain-Biased Technological Change in Thailand

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Abstract

Over the past few decades, the significant rise in Thai female labor force participation has likely been driven by technological changes that favor women's innate abilities and a broader shift in labor demand from brawn-intensive to brain-intensive skills. This study examines women's employment transitions by investigating the ripple effects of brain-biased technological change (BBTC) on employment and wage outcomes for Thai women between 1985 and 2024. To address endogeneity concerns, we employ an instrumental variable (IV) strategy alongside a pseudo-panel approach to estimate the impact of BBTC on wages. Specifically, we estimate the return on skills and the gender wage gap. Our results show that the return on skills was positive from 1994 to 2024, accompanying the decrease in the gender wage gap. Moreover, we find that the recent technological change in the labor market, as measured by the stock of robots and computer usage, are complements and substitutes with workers. Robot adoption has helped to reduce the gender wage gap, whereas computer usage has contributed to increasing gender inequality.

JEL Classification Code: E23; I24; J16; J23; J24

Keywords: Brain-biased technology change; Female labor supply; Ripple effect; Female employment transition

1. Introduction

In recent decades, one of the significant social phenomena has been the increase in female labor force participation and education attainments, accompanied by the decrease in the gender wage gap (Black & Spitz-Oener, 2010; Albanesi, 2020). Many studies have drawn attention to the return on education and skills in explaining income inequality (Katz & Murphy, 1999; Autor et al., 2006). Notably, the rapid advancement of technology has widened wage inequality by increasing the returns to high-skilled workers relative to those with lower skill levels (Author et al., 2008; Dustmann et al., 2009; Author and Dorn, 2013). With the evolution of technology, Autor et al. (2003) have proposed that skill-biased technological change (SBTC) can explain job polarization and that technology can replace the workforce in routine tasks but not in non-routine tasks. Many studies in different countries have supported Autor's hypothesis (e.g., Goos and Manning, 2007; Park et al., 2023).

Technological progress has also provided an opportunity for disadvantaged workers in the labor market and enhanced their returns to skills (Arntz et al., 2025). Building on the SBTC framework, Rendall (2017) argues that technological transitions favoring women's innate abilities, along with a shift in labor demand from brawn (physical) skills to brain (cognitive) skills, known as the brain-biased technological change (BBTC) may help explain the transition in female employment and the rise in their wages. Based on the literature, BBTC, which has focused on the brain over brawn inputs, began in the 1960s, while SBTC, which has focused on the increasing demand of cognitive skills, education, and technical expertise, emerged in the late 1970s. Ge and Zhou (2020) further explain that as new technologies interact differently with various skill types, it may influence the demand for those skills differently, leading to different impacts on male and female wages.

Over the three decades spanning the 1980s to the 2000s, Thailand's economy has undergone a significant structural transformation from an agricultural-based economy to a manufacturing and service-oriented economy (Vanitcharearnthum 2019; Paweenawat and Liao 2024a). During 2010s, the country introduced "Thailand 4.0" initiative, aiming to escape from the middle-income trap, adapt to the global shift, and transform the economy through innovation and digitalization, focusing on high-tech industries (Jones and Pimdee, 2017; Tang, 2024). In 2020, Thailand ranked 13th among the world's top 15 robotics markets, with 29,000 industrial robots installed (Sangsubhan et al., 2023). The increasing adoption of industrial robots can be attributed to two key factors: the declining costs of robotic technologies and growing labor shortages exacerbated by demographic aging. According to the International Federation of Robotics (IFR, 2021), Thailand has experienced particularly rapid growth in industrial automation, with robot installations in manufacturing facilities increasing at an average annual rate of 23% over the past decade.

In 2023, the digital economy contributed 6% of Thailand's GDP, or about $36 billion, and is projected to grow to 11% of GDP by 2027 (U.S. Department of Commerce, 2024). Thailand has made progress in robotics adoption by using around 3,300 robots, making the country the 14th most prominent user of robots globally and the second in Southeast Asia, following Singapore (International Robotics Federation, 2024). In the meantime, computer usage across various industries has continuously increased. The recent survey by Thailand's National Statistical Office (NSO) (2022) reported that in 2022, around 1,053,845 establishments, or 41.2%, reported using computers.

Although technology adoption has been rising across various industries in Thailand, few empirical studies have explored how technological advancement affects the country's labor market. For example, Jongwanich et al. (2022) showed that technology influences the shift between skilled and unskilled jobs, especially in capital-intensive

industries like automotive and electronics, while Paweenawat (2022) highlighted the rising demand for skilled workers in the Global Value Chain (GVC)-linked sectors, increasing returns to high skill. However, only one study by Paweenawat and Liao (2024b) integrates the gender perspective, despite the fact that women in Thailand have become the main workforce, associated with a substantial rise in female labor supply in recent decades (Paweenawat & McNown, 2018) and their real wages have steadily increased over time (Paweenawat & Liao, 2021). Paweenawat and Liao's (2024b) study strongly insists that Thai women benefit more from the shift towards brain skills, with higher returns and better job matching than men.

The main objective of this study is to investigate employment transitions among women and assess the transitions in response to the technological changes over the last four decades in Thailand. Specifically, we examine the ripple effects of the brain-biased technological change (BBTC) (or the transition from brawn to brain skill in the labor market in Thailand) on employment and wages in empowering Thai women during 1985-2024.[1] The ripple effects triggered by BBTC can spread through the economy as workers move from declining industries to growing ones, potentially affecting wages, employment rates, and skill requirements across the labor market.

Our study is a comprehensive analysis incorporating both descriptive and empirical analyses. We utilize the individual levels from Thailand's Labor Force Survey, covering all regions and being nationally representative. We begin our study with the descriptive analysis section extending from Paweenawat and Liao (2024b) in terms of extending the time frame period from 1985 to 2024 and disaggregating the analysis by gender to examine trends in brain vs. brawn skills concerning Thailand's stages of economic development. In the empirical analysis, we then examine various measures

[1] The ripple effects refer to the series of interconnected and subsequent impacts that changes in one part of the labor market can have on other parts. It covers the change across the labor market, such as reshaping wages, job structures, and economic inequality

of skill, including years of education, skill levels (classified by occupation), and brain/brawn skill indices (constructed based on occupation and industry location). To investigate this, we first estimate the returns to different types of skills using three measurement approaches. To address potential endogeneity, we employ instrumental variable (IV) techniques and a pseudo-panel approach in the analysis.[2]

Finally, we expand our scope of study to consider how technological advancement, specifically the adoption of industrial robotics and computer utilization in industries, has recently contributed to the gender wage gap in Thailand. We first examine trends in the gender wage gap over this period and explore the underlying factors determining this gap. Specifically, we assess whether technological advancements, particularly robotics adoptions and computer usage, have contributed to widening or narrowing the gender gap. In particular, we estimate the returns to robotics (which may favor women or disadvantage men) and to computer usage (which may disproportionately affect women) and then apply the Oaxaca-Blinder decomposition method to quantify the extent to which robotics and computerization contribute to the observed gender wage gap.

This study contributes to literature in several ways. First, the paper provides the first analysis of the ripple effects of BBTC in Thailand using comprehensive and available individual data for over four decades (1985-2024), which captures the change of Thai female employment over time. Second, distinct from existing studies, the analysis covers Thailand's economic structural transformation by observing the changes from reliance on agriculture, manufacturing oriented economy, and a growing emphasis on services and digital economy. Third, the study provides empirical estimates of relationship between different skills (measured by education, occupation and brain and brawn job categories) and wage by employing instrumental variable (IV) and pseudo

[2] Note that we focus on the period from 1994 to 2024, as these years provide consistent data coverage and a sufficiently large sample size.

panel approach to account for endogeneity. Besides, we offer empirical analysis on the impact of robots and computer adoption on wages and the gender wage gap. Lastly, our results add evidence to the literature on female employment transition in developing countries, which are not only applied to Thailand but also to other ASEAN countries experiencing the structural change and global megatrends.

2. Literature review

The canonical model of skill-biased technological change (SBTC) has been introduced by Katz and Murphy (1992), which has been argued that it has not accounted for the polarization of employment (Acemoglu and Autor 2011). The nuanced version of SBTC has been introduced by Autor et al. (2003), indicating that routine tasks of labor can be replaced by technology but non-routine tasks cannot, which generates the polarization of employment. Rendall (2017) referred to a phenomenon called "brain-biased technological change" (BBTC) in which technological progress aligns closely with women's inherent strengths in a labor market shift away from physical tasks (brawn) toward intellectual tasks (brain). More specifically, women tend to benefit from rising returns to brain skills due to their comparative advantage in brain skills complemented with their education; all this may account for women's increased participation in the workforce and rising wage levels.

While Goldin (1990) has suggested that physical abilities contribute to lower income for women in the manufacturing sector; Galor and Weil (1996) have found that more women have joined the labor force when technological change shifted labor demand to brain skill requirements. Mulligan and Rubinstein (2008) have found that in US women's wage, as well as wage inequality have increased from the end of the 1970s that has prompted more skilled women making investments in education, thereby changing the structure of workforce. Theoretically, with the decrease of return on brawn

skills and the increase of return on brain skills, women's relative advantage in intellectual abilities contributes to the rise of employment and income levels (Rendall 2017).

Galor and Weil (1996) state that women began to enter the labor market when technological advancements impacted the reduction of the demand for physical strength (brawn) in jobs. Levy and Murnane (2003) mentioned that recent technological changes in the skill requirements of occupations, especially the impact of computers, have primarily affected the demand for college-educated workers.

Ge and Zhou (2020) mentioned that technological advancements reshape the future of work. Two key drivers of this shift are industrial robots and computing technologies, which have seen rapid progress since the 1990s. Ge and Zhou (2020) strongly mentioned that computers are prone to replace brain skill tasks, women's comparative advantage, while robots tend to substitute brawn skills, which is men's comparative advantage. They found that the negative impact of industrial robots on male wages is more substantial than on female wages, resulting in a narrowing gender wage gap. Furthermore, the negative impact of computing equipment led to decreased wages for both genders, but more pronounced for women, widening the gender wage gap.
Acemoglu and Restrepo (2017) found that the rise in robot adoption reduced employment levels and wages as robots could substitute for routine manual labor, particularly among less-educated men working in blue-collar roles, such as manufacturing and assembly line positions. However, robot adoption adversely impacts particular industries (e.g., automotive manufacturing).

Black and Spitz-Oener (2010) mentioned that using computers can explain approximately 40 percent narrowing the gender wage gap in the West German labor market. Occupational choice, cultural, social, and intergenerational learning on female

labor supply also contribute to the gender wage gaps (Hsieh et al.,2013; Fogli & Veldkamp, 2011). Ngai and Petrongolo (2017) have suggested that the diminishing gender wage gap and employment gap can be explained by structural change. When brawn skills are more valuable, women with high intellectual abilities tend to stay out of the labor market and then having less education than men with same innate brain skills. Conversely, when brain skills are more valuable, more women will get into the labor market and over time surpass men in education levels due to their relative advantage in brain skills (Jones et al. 2015; Rendall 2015).

Regarding studies in Thailand, few previous empirical studies have examined the impact of technological advancement on Thailand's labor market in terms of influencing employment dynamics and wage structures in the country. Jongwanich et al. (2022) found that technological advancement does not significantly drive workers out of the job market but leads to reallocation between skilled and unskilled roles, and the effect is strong in industries that rely heavily on capital, such as automotive, electronics, and machinery. However, they found a decline in wages in some sectors. At the same time, Phaokrueng (2023) found the positive impact of information and communication technology (ICT) policies since 2010 on reducing wage inequality among Thai households. Paweenawat (2022) found that the higher demand for skilled workers in the global value chain (GVC)-oriented industries explains the increasing return on skills for workers in Thailand. However, most studies overlook gender despite women's growing role in the workforce. Only Paweenawat and Liao (2024b) address this, showing that Thai women benefit more from the shift toward brain skills, with higher returns and better job matching than men. However, the paper faced severe problems as it did not adequately address the endogeneity in estimating the return on skills, which we will address in this study. In addition to estimating the returns to brain and brawn skills, this paper also incorporates the adoption of robots and computer usage, its impact on wages, and its contribution to the gender wage gap in Thailand.

3. Data

In this study, we use the third quarter of Labor Force Survey (LFS) of Thailand from 1985 to 2024 conducted by National Statistical Office (NSO) to analyze the female employment transition and return on their skills in Thailand. The sample is restricted to workers aged 15-60 years old. The cross-sectional LFS contains detailed individual information, including age, education levels, wage, occupations, industries, marital status, work status, residence area, and so forth, which is suitable for our analysis. We apply three skill measurements in this study. In addition to the levels of education and occupations[3], we constructed the brain and brawn skill index based on both occupations and industries information to capture the return on skills and provide additional insights to the labor market transition in Thailand. Relying on the assumption that occupations and industries in Thailand demand similar skills as in the US, we map the job requirements from the Dictionaries of Occupational Titles (DOT) 1991 to the LFS following Rendall (2013).The brain skill is generated based on broad categories on standardized general educational development and specific vocational training in DOT and the brawn skill is generated based on the physical strength requirements and environmental conditions (Rendall, 2011; Paweenawat and Liao, 2024b).

In the estimation section, we divide the 30 years (1994-2024) into three main phases, aligned with key stages in Thailand's economic development. The first phase spans from 1994 to 1997, which we call the manufacturing-oriented economy.[4] The second phase spans from 1998 to 2015, a period marked as the recovery stage from the Asian

[3] The occupations are assigned to three levels of skill following Autor (2019) and Paweenawat and Liao (2024b): managers, legislators, professionals, and technicians as "High skill", clerks, service workers, and plant and machine workers as "Middle skill", and craft workers, agricultural workers, and unskilled workers as "Low skill".

[4] During this period, Thailand has been among East Asian experiencing rapid economic growth, averaging over 8% annually (Vinod & Peter, 1994). The economy is export-led, primarily driven by computers and electronic parts (Phongpaichit, 2015). Until the 1997 crisis, the country's economy has already adjusted from agriculture to manufacturing labor-intensive industries (Siamwalla, 2000).

Financial Crisis in 1997 and the country shift toward service-driven economy.[5] The third phase spans from 2016 to 2024, as the country intend to escape the middle-income trap country to a high-income country, the country introduced "Thailand 4.0", developing a knowledge-driven economy that emphasizes research, technology, and innovation (Royal Thai Government, 2016).[6]

Table 1 shows the summary statistics of LFS 1994 to 2024 for the analysis.[7] The wage has increased from the first time period to the third time period. In the first two time period, male's wage is higher than female' wage, while in the latest time period, female's wage has surpassed male's wage on average. On average, the wage and years of schooling has increased over the four decades for both female and male, while men's year of schooling has increased slower than female. The brawn skill index is higher for male than female, while brain skill index is higher for female than male. The number of children has decreased during the time for both female and male.

[Table 1]

In addition, to assess further the effect of technology progress in robotics adoption on the labor markets, we will explore the information on robots from the International Federation of Robotics (IFR). Due to the data limitation, we used IFR from 2010 to 2019. Despite that Thailand began using industrial robots in the late 1990s, the widespread adoption of robots started around 2010, which makes our period covering

[5] With assistance from the IMF, Thailand implemented structural reforms, particularly in the banking and financial sectors (Sussangkarn, 1999; Jungjaturapit, 2008). As exports slowed down, the services sector, particularly tourism, increasingly contributed to driving the country's economic growth (Sondergaard et al., 2016). Despite these shifts, Thailand fell into the "middle-income trap" country (Jitsuchon, 2012).

[6] During this period, transitioned from low-cost manufacturing to high-value innovation, turned primitive agriculture into smart farming and agri-tech, and added value-based services in service sectors (Royal Thai Government, 2016; The Government Public Relations Department, 2016). The primary focus on digital transformation is the Eastern Economic Corridor (EEC) (or Infrastructure megaproject in Chonburi, Rayong, Chachoengsao) (World Bank, 2019). However, while the country was hit hard by COVID-19 during 2020-2022, which significantly impacted the tourism sector, the digital economy accelerated in both government and private sectors, primarily through e-commerce, online education, remote work, and cash transfer programs from the government.

[7] We have dropped those who do not report the information on factors considered in the analysis.

the significant transformation of robot adoption in Thailand. In addition to robotics, computer usage extracted from the survey of Information and Communication Technology (ICT) from 2019 to 2023 conducted by NSO is used to account for computer usage at the industry level. Computers have fully integrated into the Thai economy and digital society during this period under the Thailand 4.0 policy. The robot's stock and computer usage at the industry level are adjusted and matched to LFS using industry code and year.

4. Descriptive analysis

As the employment transitions toward skill-intensive roles structurally associated with wage distributions, we first provide the analysis on employment transition from 1985 to 2024 and then present the wage transition during this time. The study begins by analyzing the changes in female labor supply and income across various skill levels and the transition of women employed in different skill levels over time. Building on the overall findings of Paweenawat and Liao (2024b), this study further integrates gender analysis to examine the distribution of brain versus brain skills.

4.1 Employment transition

We first provide an overview of employment transition by different occupational skills and gender. Figure 1 presents the share of employment by skill level among men and women from 1985 to 2024. Specifically, Figure 1(1) illustrates the share of low-skill employment. Women have a lower share of low-skill employment than men, and the gap has widened over the last four decades, indicating more women have moved up to middle- or high-skill employment. The share of low-skill employment for women has dropped from 46% in 1985 to 32% in 2024. Figure 1(2) shows the share of middle-skill employment; the share for men and women has been similar in the first decade, and

women have accounted for higher shares from 1994. The gap between men and women has remained stable in recent decades. Figure 1(3) displays the share of high-skill employment. The changes in high-skill employment are more stable for women, where the share has increased from 6 percent in 1985 to 11 percent in 2024. After the Asian financial crisis in 1997, the share of men in high-skill employment decreased significantly, while the share of women in high-skill employment has not been affected much. From 2017, the share of women in high-skill employment has exceeded men and the gap has widened in recent years.

[Figure 1]

Figure 2 further disaggregates the workers into full-time and part-time workers. The full-time workers are defined as those who work over 35 hours a week (Paweenawat and Liao, 2024c). The trends for full-time workers are similar to those in Figure 1 for all three levels. In contrast, part-time workers show a higher share in low-skill employment and a lower share in middle- and high-skill employment. In 1997, there was a significant drop in low-skill employment and an increase in high-skill employment. The 1997 Asian Financial Crisis hit Thailand's labor-intensive sectors hardest, leading to mass layoffs and reduced demand for low-skill part-time workers. Moreover, the crisis has compelled Thailand to shift its focus toward higher-value industries and to increase demand for part-time, high-skill workers.

[Figure 2]

Figure 3 and Figure 4 provide the average score of brawn and brain skills for men and women from 1985 to 2024, respectively. The brawn skill index for women has decreased from 1.1 in 1985 to 0.8 in 2024, while the index for men has been relatively stable in Figure 3. The gap between men and women has increased in recent two decades. However, Figure 4 shows there is a rise of brain skill index for both men and women from 1985 to 2000 and then it has decreased. In recent two decades, women have a higher score in brain skills than men and the gap has continued to widen.

[Figure 3]

[Figure 4]

Figure 5 provides the average years of schooling for men and women during last four decades. Women's years of schooling have increased from 5.6 in 1985 to 9.9 in 2024, which has exceeded men after 2017, indicating that the education has grown faster for women than men.

[Figure 5]

Figure 6 provides the change in shares of employment by industries and gender between 1985 and 2024. The employment in Thai labor market has transmitted from agriculture sector to manufacturing and service sector, which has associated with the changes in worker's wage. The industrial structure has changed significantly during the time and female workers has undergone a more dramatic change than male workers. Higher share of female workers has moved from agriculture sector to manufacturing and service sector. The share of employment in agriculture has decreased 42 percent for female and 28 percent for male, while the share of employment in service has increased 45 percent for female and 25 percent for male.

[Figure 6]

4.2 Wage transition

Next, we provide an overview of changes in wages by gender overtime. Figure 7 shows the change of real log hourly wage by skills and gender during 1985 to 2024. Generally, average wage of all groups has increased throughout the time and high-skill workers have the highest wage among the skill groups. While men have obtained higher wage in low- and middle-skill group than women, the gender wage gaps have narrowed in recent years. For high-skill group, the gender gap has diminished in the recent decade. According to Paweenawat (2022), the increasing demand for high-skill workers in global value chains (GVCs)-oriented sectors has resulted in higher wage premium for the group.

[Figure 7]

Figure 8 presents the change of real log hourly wage by years of schooling and gender from 1985 to 2024. From 1985, women's wages by years of schooling have increased faster than men's, and eventually, women's wages have caught up with men's wages in 2014. In the recent decade, women's average wage has been higher than men's wage.

[Figure 8]

To see the effect of robots on male and female workers, we match the LFS with the industry-level data on stock of robots from the International Federation of Robotics (IFR). Due to the data limitation, we use the data from 2010 to 2019. Figure 9 shows the stock of robot usage and newly added robot installation in manufacturing from 2010 to 2019. There is a sharp increase of stock of robot usage in manufacturing during the time. Then, in figure 10, we present the growth rate of wage for male and female workers in manufacturing at the same time period. The growth rate of wage is generally faster for female than male in manufacturing, suggesting that male is more likely to be affected by automation through robot usage than female. For both male and female workers, after 2012, the growth rate of wage in manufacturing sector has dropped significantly and remained at a relatively low level.

[Figure 9]

[Figure 10]

5. Methodology

5.1 Return on skills

The fundamental model to estimate the relationship between skills and wage is based on the Mincer wage regression (Mincer, 1974):

$$lnw_i = X_i\delta + S_i\beta + \varepsilon_i \quad (1)$$

where w_i is the wage of individual i, X_i captures the individual's characteristics, including age, age square, number of children, marital status, residence area, industrial sectors, occupations, time effects and regional dummies. S_i indicates the skill requirements, which are based on educational attainments (occupations or constructed variables that measure the brain and brawn skill content of occupations and industries illustrated in section 3). β measures the association between skills and wages. Building on foundational work by Katz and Murphy (1992), the Mincerian model suggests that while technological changes alter labor allocation across sectors, wage changes fundamentally reflect the change in skill pricing (Acemoglu and Autor, 2011).

To account for the endogenous issues, we employ two different methods including IV and pseudo-panel approach. Specifically, for IV approach, we exploit the education reform of Rajabhat University[8]:

$$S_i = R_i\alpha_1 + X_i\alpha_2 + \varphi_i \qquad (2)$$

where R_i is the education reform that has upgraded teachers' training college to Rajabhat university. X_i is a vector of the controlling variables including age, age square, number of children, marital status, residence area, industrial sectors, time effects and regional dummies. The instrument has passed all tests of the IV, making it suitable for use in the estimation. Data from the Office of the Higher Education Commission (OHEC) (2013) shows that Rajabhat University's student enrollment grew significantly, rising from around 300,000 in 1995 to over 570,000 by 2012. Warunsiri and McNown (2010) suggests that the expansion of Rajabhat Institutes has made higher education more accessible and affordable, thereby increasing enrollment demand. As

[8] The reform has upgraded the historical teachers' training college to Rajabhat Institutes in order to promote higher education (Paweenawat and Liao, 2023).

of 2019, Thailand's higher education system includes 38 Rajabhat universities, all operating under the country's Higher Education Institutions framework (OHEC, 2019).

For pseudo-panel approach, we extend the estimation of return to schooling based on Warunsiri and McNown (2010) to returns to brain and brawn skills. According to Deaton (1985), group estimates of linear model for repeated cross-section data can be consistent and estimation using group data can be served as 2SLS for individual data (Angrist, 1991; Devereux, 2004). The approach has since been widely adopted to estimate returns to education across developing countries (Oryoie and Vahidmanesh, 2021 for Iran; Zhang and Alwang, 2019 for Zimbabwe; Bhattacharya and Sato, 2017 for India; Malik & Awan, 2016 for Pakistan; Tran and Paweenawat, 2023 for Vietnam; Himaz and Aturupane, 2016 for Sri Lanka).

To construct the pseudo panel, we define ten-year birth cohorts, five regional groups interacting with 40 survey years. The equation in terms of group average becomes:

$$\overline{lnw_{ct}} = \overline{X_{ct}}\delta + \overline{S_{ct}}\beta + \alpha_c + \overline{\varepsilon_{ct}} \qquad (3)$$

where $\overline{lnw_{ct}}$ is the mean of log hourly wage for women in cohort c at time t. $\overline{S_{ct}}$ represents the mean of brain (brawn) skill for for women in cohort c at time t. $\overline{X_{ct}}$ is the mean of controlling variables and α_c is the cohort fixed effect. Following Pencavel (1998) and Paweenawat and McNown (2018), we use the weighted least square (WLS) to account for the heteroscedasticity among different observations within each cohort.

5.2 Gender wage gap

To investigate the gender wage gap during the time, we employ the Blinder-Oaxaca decomposition approach, which divides the gap of log wages into explained component and unexplained component (Oaxaca, 1973; Blinder, 1973). The wage equations are divided into female and male groups:

$$Y_i^M = X_i^M \beta_i^M + \varepsilon_i^M \qquad (4)$$

$$Y_i^F = X_i^F \beta_i^F + \varepsilon_i^F \qquad (5)$$

where Y_i indicates the log hourly wages of male (M) and female (F), X_i is the vector of controlling variables, including brain and brawn skills, age, age squared, number of children, marital status, regional dummies and year effects. The coefficient β_i is obtained by using OLS estimation and the mean values of wage for the male and female groups are estimated. After deducting the means of the two groups:

$$\overline{Y}^M - \overline{Y}^F = \overline{X}^M \beta^M - \overline{X}^F \beta^F = \beta^M (\overline{X}^M - \overline{X}^F) + \overline{X}^F (\beta^M - \beta^F) \qquad (6)$$

Equation (6) shows that the gender wage gap consists of two components: the first part indicates the effect of gender difference in explanatory variables, and the second part is the unexplained differential.

6. The effect of skills on wage and gender wage gap

6.1 IV estimations

Table 2 presents the return on years of schooling using IV model. The effect of years of schooling has generally shown a positive impact on wage. Except for the second time period, the effect is statistically significant for female. In the third time period, the return on years of schooling is higher for female than male (0.102 to 0.0892). These results confirm that the digital economy era favors the return to education for women, as Rendall (2017) argues that technological advancement changed the demand from physical labor to intellectual abilities, which women have comparative advantages over. The number of children shows a negative effect on female and male wages, while being married has a positive effect on their wages, consistent with the estimated children's impact on married women's wages in Thailand by Liao and Paweenawat (2021).

[Table 2]

Table 3 shows the return on skills using IV model. The return on skills shows a positive effect on female's wage for the three time periods, indicating that obtaining higher level of skills promote female's wage (1.668, 0.635, 1.040). Compared to other developing countries, Thailand's economic structure change from an agriculture-based economy to an industry and service-based economy has increased Thai women's participation and wages in the labor market due to work flexibility that is more in line with their skills and abilities (Rendall, 2013). For male, the significant positive effect of skills appears in the second and third time period. Compared female to men, during 1998 to 2015, the effect of skills is higher for male than female, while during 2016 to 2024, the effect is higher for female than male. This long-term trend is consistent with Rendall (2017) mentioning that women's initial entry into the labor market does not yield high returns at first, but over time, as women's cognitive advantages and educational attainment increase, they outpace men in college completion, resulting in a positive effect finally. The Thai female workforce has therefore made significant progress in university education, in which the share of female workers with university degrees has greater than the share of female workers (World Bank, 2022).

[Table 3]

Table 4 presents a detailed analysis of the high-tech and low-tech industries using IV estimation, defined based on the International Standard Industrial Classification (ISIC) Revision 4, following the OECD R&D intensity taxonomy (Galindo-Rueda and Verger, 2016). The results show that the return on the years of schooling is positive for both males and females in the high-tech industry, while it is negative for females in the low-tech industry. Compared to males in the high-tech industry, the positive effect is higher for males, indicating that education increases males' wages more than females', and the gender wage gap may expand in this sector. In contrast, the return on skills indicates that in high-tech industries, women's skills are rewarded, resulting in a relative

advantage for women, while men are penalized. However, in low-tech industries, men's skills are still valued and retain an advantage over those of women.

[Table 4]

Table 5 shows the return on skills using IV by married and unmarried women. The return is positive and higher for married group than unmarried group, indicating that married women benefit more from higher skills.

[Table 5]

6.2 Pseudo-panel approach

Table 6 presents the return on brain and brawn skills using the pseudo-panel approach. For the brain skills, the positive effect is statistically significant in the second and third periods for both females (columns 2 and 3) and males (columns 5 and 6), and the effect of brain skills has a larger magnitude for female than male (2.205 to 1.062; 1.112 to 0.611), suggesting that brain skills increase female's wage more than male's wage. The brawn skill negatively impacted female wages from 2016 to 2024, while the effect was adverse for males except for the second period. Over decades, changing employment patterns in the labor market due to technological developments have increased the demand for high-skilled labor, shifting from emphasizing physical skills to intellectual skills, benefiting female workers more (Paweenawat and Liao, 2024b).

[Table 6]

The results are consistent with the "brain-biased technological change" (BBTC) found by Rendall (2017), in which technological progress aligns closely with women's inherent strengths in a labor market shift away from physical tasks (brawn) toward intellectual tasks (brain). More specifically, women tend to benefit from rising returns to brain skills due to their comparative advantage in brain skills complemented with

their education; all this may account for women's increased participation in the workforce and rising wage levels. In summary, the interaction between different types of technological change plays a crucial role in influencing the evolving selection of women into the workforce, ultimately shaping the education trajectory and wage gap convergence over time.

6.3 The gender wage gap

Table 7 shows Blinder-Oaxaca decomposition results. Column 1 and 2 shows that the gender wage gap is positive in the first two time periods, indicating male has a higher wage than female during 1994 to 2015. Both the explained part and unexplained part are positive and contributed to increase the gender wage gap during the time. In the explained details, brain skills have a negative effect on the gender wage gap, suggesting that higher brain skills have contributed to decrease the gap. In column 3, the latest time period has shown a negative total difference, suggesting that female has a higher wage than male. This result is consistent with Paweenawat and Liao's (2022) finding that the gender wage gap in Thailand has narrowed over time, mainly due to higher levels of education among women, a shift toward employment from agriculture to manufacturing and service sectors, and an increasing number of women in professional careers.

[Table 7]

The unexplained components still contribute to increase the gap, while the explained components help to decrease the wage gap during the time. Both the brain skills and brawn skills have contributed to reduce the gender wage gap in the explained details. Consistent with Rendall (2013) and Paweenawat and Liao (2024b), the results suggest that the employment transformation of Thai labor market has benefited female with better opportunities and work flexibility to match their innate abilities in the labor market during the time periods.

Columns 4 and 5 provide detailed analysis for the high-tech and low-tech industries. The results show that in both high-tech and low-tech industries, the gender wage gap remains positive, and the gap is larger in the high-tech industry than in the low-tech industry, which is consistent with our assumption. In the explained part, brain skill shows a positive effect on the gender wage gap in the high-tech industry, while it has a negative effect in the low-tech industry. The brawn skill shows a negative effect for both industries. However, while skill can help to close the gender wage gap, the unexplained part suggests that the level still mainly contributes to gender inequality.

7. The effect stock of robots and computer usage on wage and gender wage gap

7.1 The effect stock of robots and computer usage on wage

Table 8 shows the return on education considering the effect stock of robots by gender from 2010 to 2019 and computer usage by gender from 2019 to 2023 using IV estimation. Column 1 and 2 perform the IV estimation for women and men with information on the stock of robots in manufacturing, while column 3 and 4 perform the IV estimation for women and men with information on computer usage at the industry level. Generally, after accounting for both factors, the effect of years of schooling remains positive and significant. The stock of robots shows a positive impact on wage and the magnitudes are relatively small for both men and women. In column 3 and 4, computer usage has shown a negative effect on male's wage suggesting that the computer usage tends to reduce male's wage, while it is insignificant for female. Table 9 shows the return on skills controlling for stock of robots by gender and skill levels using IV estimation. The effect of robots remains significantly positive for middle- and high-skill women, and low- and middle-skill men.

[Table 8]

[Table 9]

Distinct from Ge and Zhou (2020), which suggests that in the US, the increase in robot and computer adoption decreases both male and female wages, our results show that robot adoption has increased their wage, while computer adoption has decreased male wages. Thus, the recent technological change in the labor market, as measured by the stock of robots and computer usage, are complements and substitutes with workers, which is likely to cause changes in the gender wage gap. Specifically, the stock of robots complemented the brain or brawn skills of both female and male workers, while computer usage is a substitute for male workers. In Thailand, Jongwanich et al. (2022) has found that robot integration in some sectors tends to create more complementary relationships with workers, and it is limited for advanced technology to substitute worker in the job market.

7.2 The effect stock of robots and computer usage on gender wage gap

Lastly, to analyze the effect of stock of robots and computer usage on gender wage gap, we apply the Oaxaca-Blinder decomposition to investigate the wage differences. In column 1 and 2 of Table 10 shows Blinder-Oaxaca decomposition results considering the effect of stock of robots and computer usage. Column 1 shows that the gender wage gap is positive during the time, indicating male has a higher wage than female during 2010 to 2019. The explained part has contributed to decrease the wage gap, while the unexplained part is positive and contributed to increase the gender wage gap during the time. Unlike the previous time periods, it shows that brain skill in the explained details has a positive effect indicating it has contributed to increase the gender wage gap, while brawn skill and stock of robots has helped to decrease the gender wage gap.

Column 2 shows that the total difference is negative during 2019 to 2023, suggesting female has a higher wage than male. While the unexplained part has also contributed to increase the gender wage gap during the time, and the magnitude of explained part

has surpassed unexplained part. For the explained details, both skills have contributed to reduce the gender wage gap, and the computer usage has shown a positive effect indicating that it has contributed to rise the gap.

[Table 10]

Generally, the stock of robots has help to reduce the gender wage gap during 2010 to 2019, and the computer usage has contributed to increase the gender inequality during 2019 to 2023. The results are consistent with Ge and Zhou (2020), which suggests that the robots adoption reduces the gender wage gap, whereas the computer adoption increases the gender wage gap.

8. Conclusion and Policy recommendations

In this study, we have focused on the ripple effect of BBTC in reshaping job structures, wages, and gender inequality. We have provided a comprehensive analysis of the return on skills and the gender wage gap in Thailand from 1985 to 2024. We extend the work of Paweenawat and Liao (2024b) and expand the time frame relating to Thailand's stages of economic development. In the empirical analysis, we examine the return on skills using various measures of skill, including years of education, skill levels, and the brain and brawn skill index, spanning the LFS period from 1994 to 2024. By applying the IV estimation and pseudo-panel approach, we have found that the year of schooling, occupational skills, and brain skills have a positive effect on workers' wages. The gender wage gap has diminished from 1994 to 2024, and in the latest time period, female obtains higher wages than males on average, and brain skills have contributed to decreasing the gap. In recent years, overeducation and skill mismatch associated with wage penalty have been found in Thailand (Paweenawat and Vechbanyongratana, 2015). Even when higher education is rewarded, the return is lower than in well-matched jobs. The government should invest more in women's education and brain

skills by expanding access to higher education and continuous skill development programs for women to maximize these returns. In addition, actions to stimulate individual incentives for female workers to engage in those programs and opportunities can be more efficient by using financial support mechanism, such as subsidies or scholarships, which can decrease the opportunity cost of obtaining skills and help female workers to keep investing in their human capital.

However, as we also found that brawn skills decrease female wages during 2016–2024, but have a mixed effect for men, this result implies that while BBTC strengthens women's advantage, relying on physical skills is a disadvantage. Therefore, government should encourage the development of brain and cognitive skills and discourage female workers' reliability on brawn skills by enhancing the employment shift from brawn-intensive jobs to brain-intensive jobs.

In addition, as we also perform disaggregated analysis, we found that in the high-tech industries, women's skills are rewarded but men's skills are penalized, implying that women gain a relative advantage. Hence, to take the advantage of technological changes in promoting female workers' status in the labor market, policies on encouraging their participation in technological innovation and adoption, especially for high-tech sectors, should be implemented.

Then, we examine the impact of the stock of robots and computer usage on the wages of both females and males. We have found that the stock of robots has a positive impact on both female and male wages, and computer usage has a negative effect on males' wages, suggesting that computer usage tends to reduce males' wages. Furthermore, we investigate the effect of stock of robots and computer usage on the gender wage gap by employing the Oaxaca-Blinder decomposition. The results show that the stock of robots has helped to reduce the gender wage gap, but computer usage has contributed to increasing the gender inequality over time. In addition, the recent technological change,

Artificial Intelligence (AI), can be an ultimate tool for task substitution in the labor market. Occupations with high brain skills can be replaced by AI. Unlike former computerization that affected male wages, AI may potentially affect women disproportionately as high share of women are employed in the occupations with cognitive skills, which will generate new risk to increase the gender inequality.

Finally, our results still indicate a strong level of discrimination in Thailand's labor market; addressing gender bias and discrimination in Thai society is a must. This could be implemented by enforcing stronger equal pay legislation and implementing inclusive workplace policies to reduce gender-based discrimination in the labor market.

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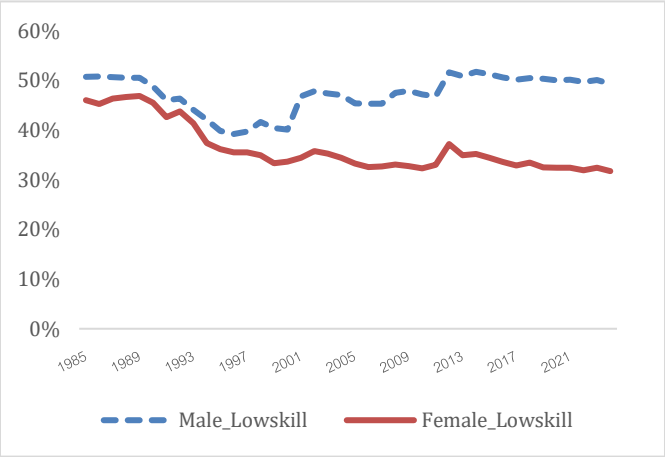
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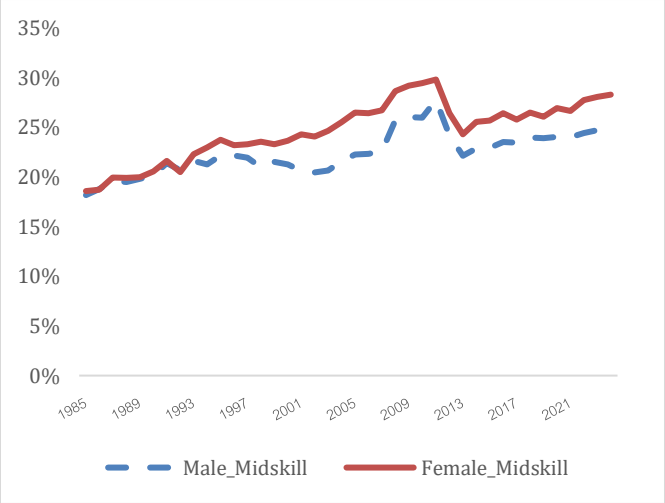
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Figure 1. The share of employment by skill level among men and women (1985-2024)

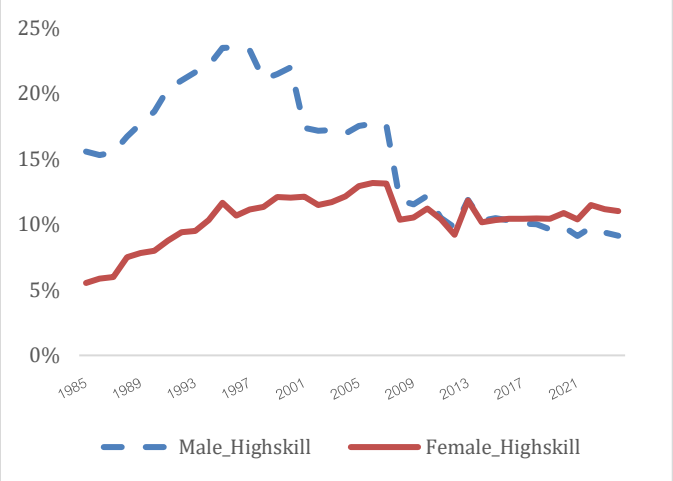
(1) Low-skill employment



(2) Middle skill employment



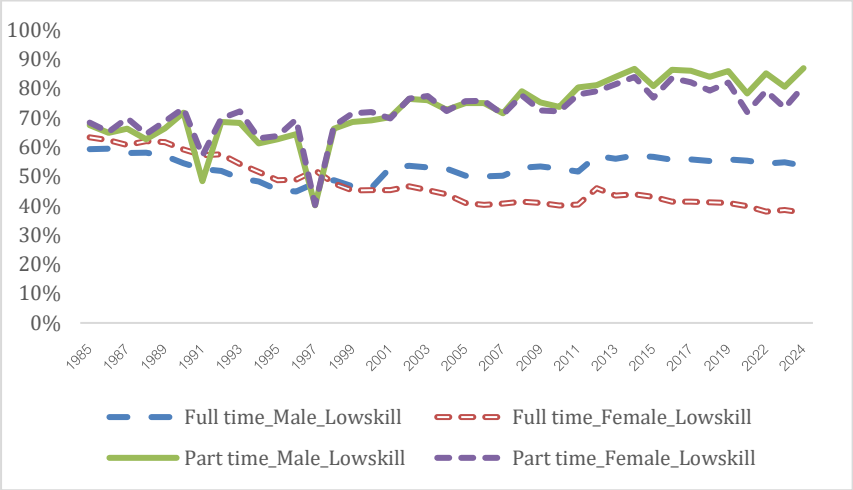
(3) High-skill employment



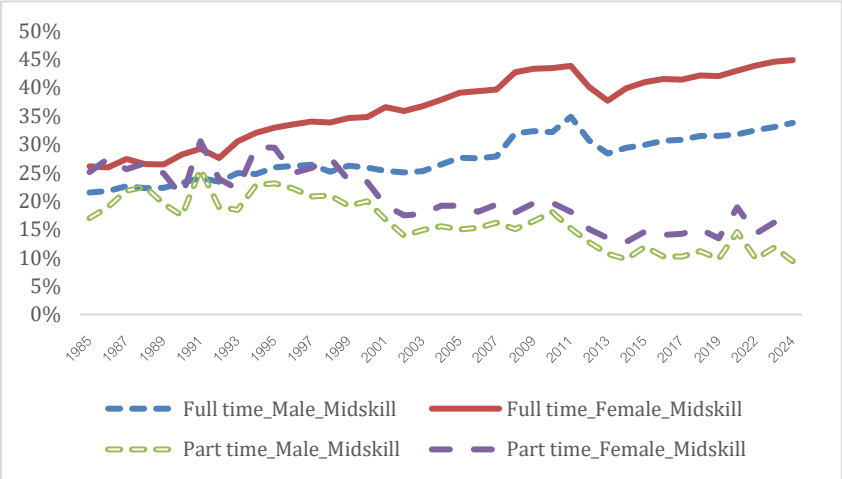
Source: Authors' Calculation from LFS (1985 – 2024)

Figure 2. The share of employment by skill level and working hours (1985-2024)

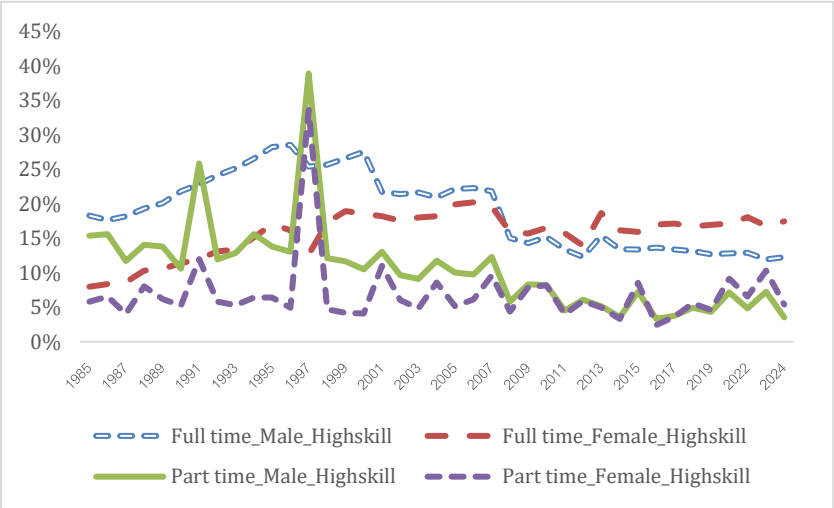
(1) Low-skill employment by full-time and part-time workers



(2) Middle-skill employment by full-time and part-time workers

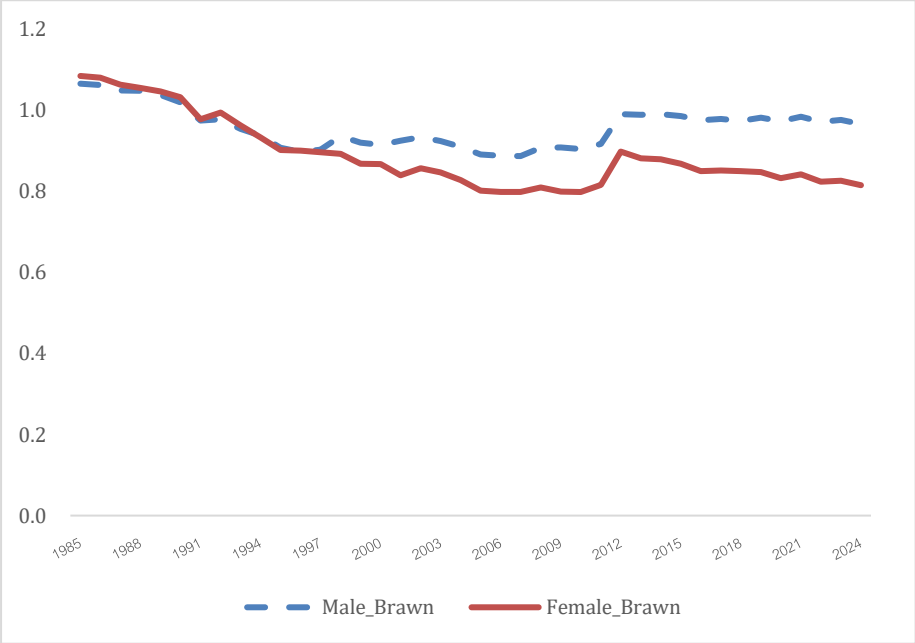


(3) High-skill employment by full-time and part-time workers



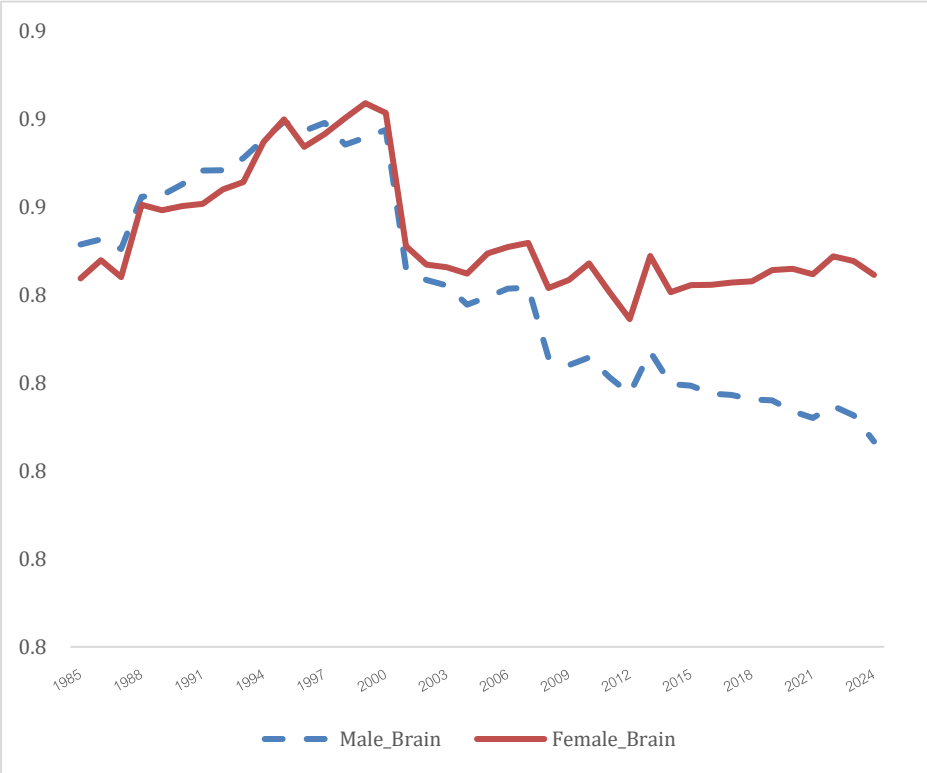
Source: Authors' Calculation from LFS (1985 – 2024)

Figure 3. Average score of brawn skills by gender, 1985-2024



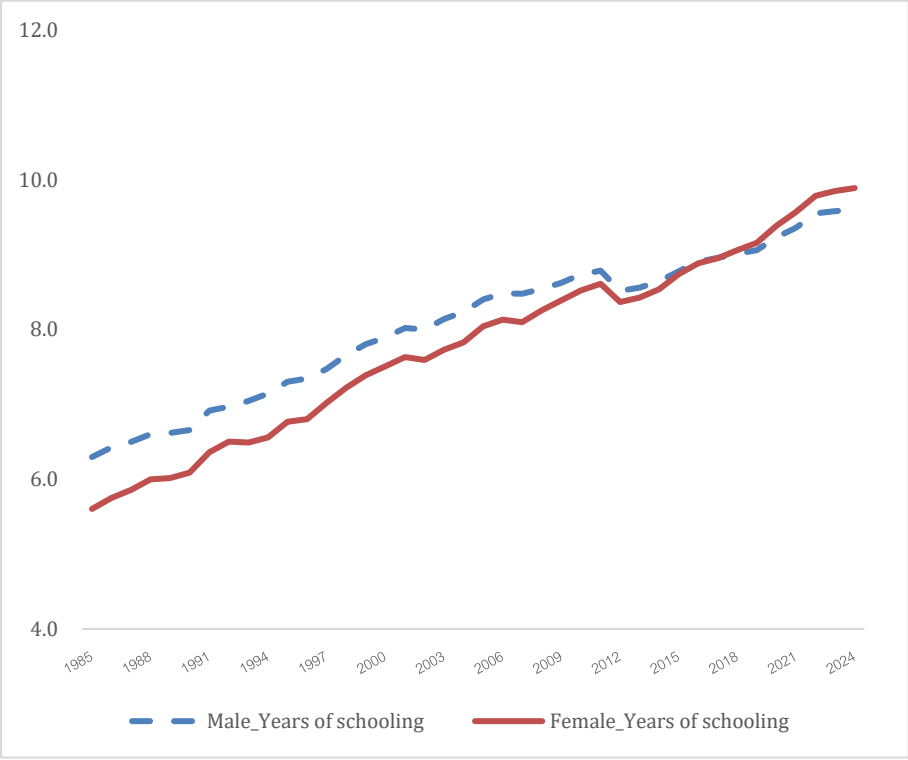
Source: Authors' Calculation from LFS (1985–2024)

Figure 4. Average score of brain skills by gender, 1985-2024



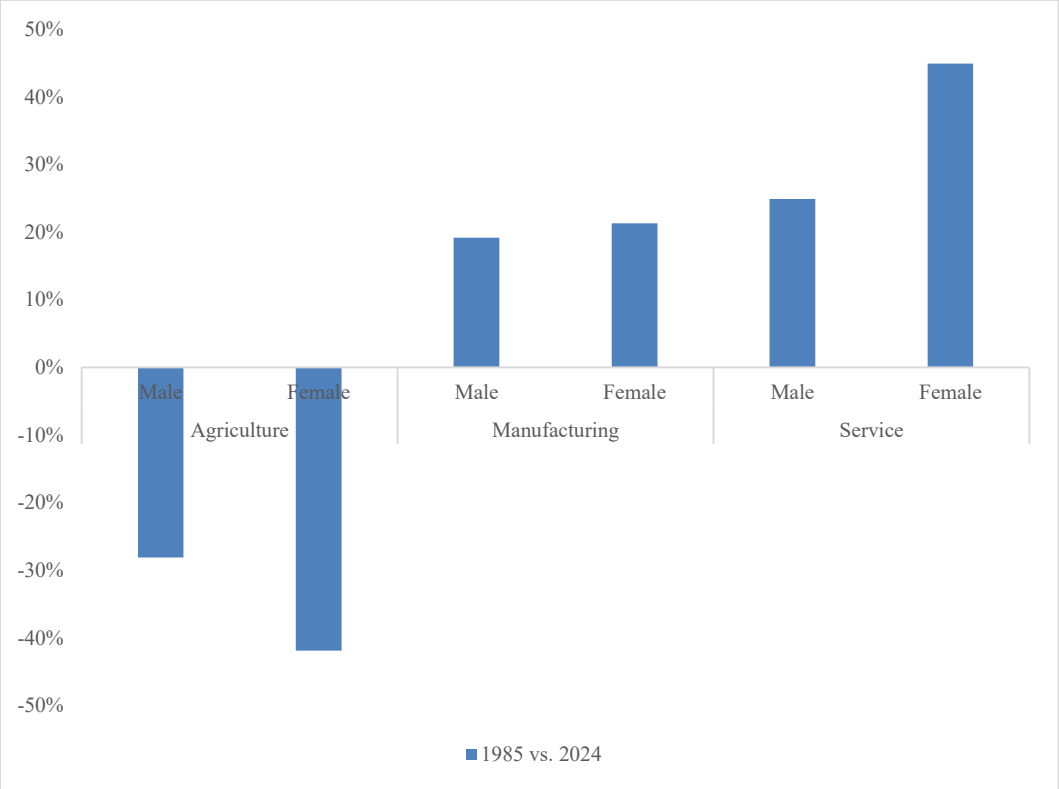
Source: Authors' Calculation from LFS (1985 – 2024)

Figure 5. Average years of schooling by gender, 1985-2024



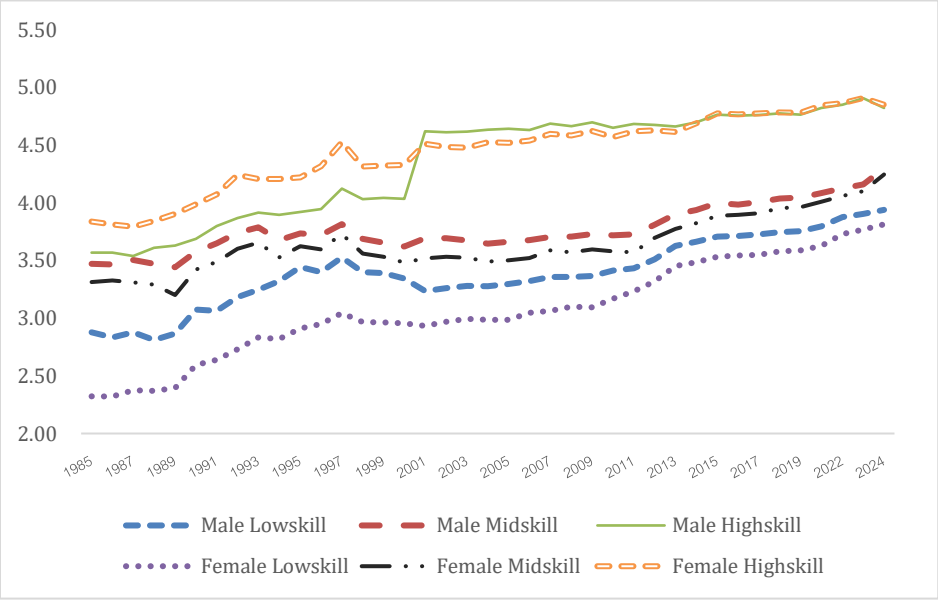
Source: Authors' Calculation from LFS (1985 – 2024)

Figure 6. Change in shares of employment by industries and gender, 1985 vs. 2024



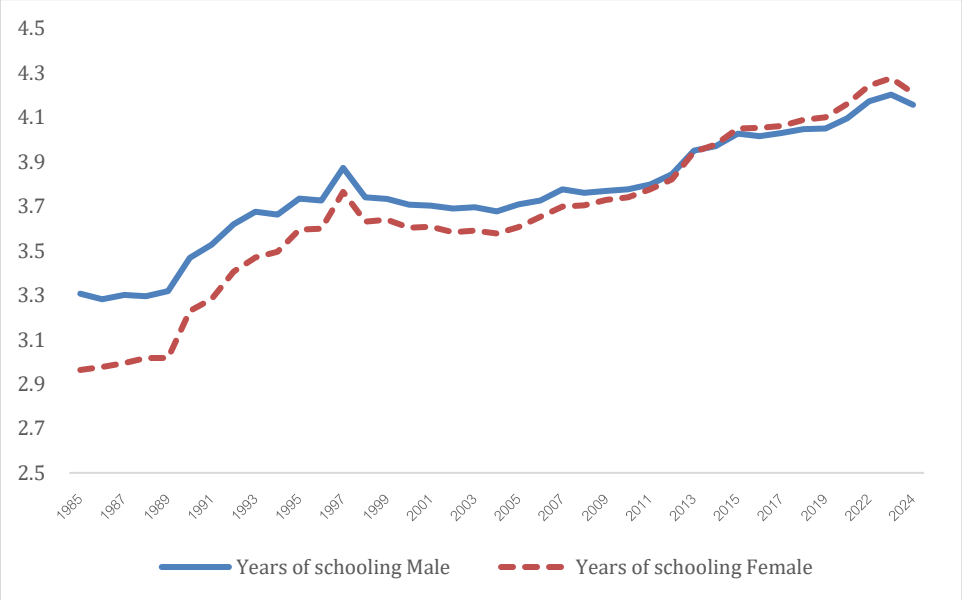
Source: Authors' Calculation from LFS (1985 – 2024)

Figure 7. Real log hourly wage by skills and gender, 1985-2024



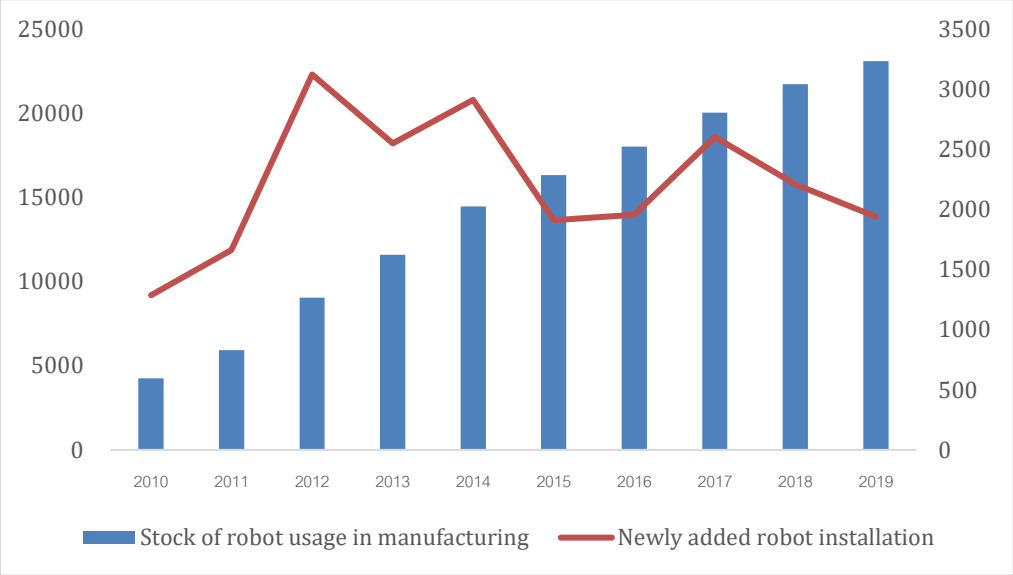
Source: Authors' Calculation from LFS (1985 – 2024)

Figure 8. Real log hourly wage by years of schooling and gender, 1985-2024



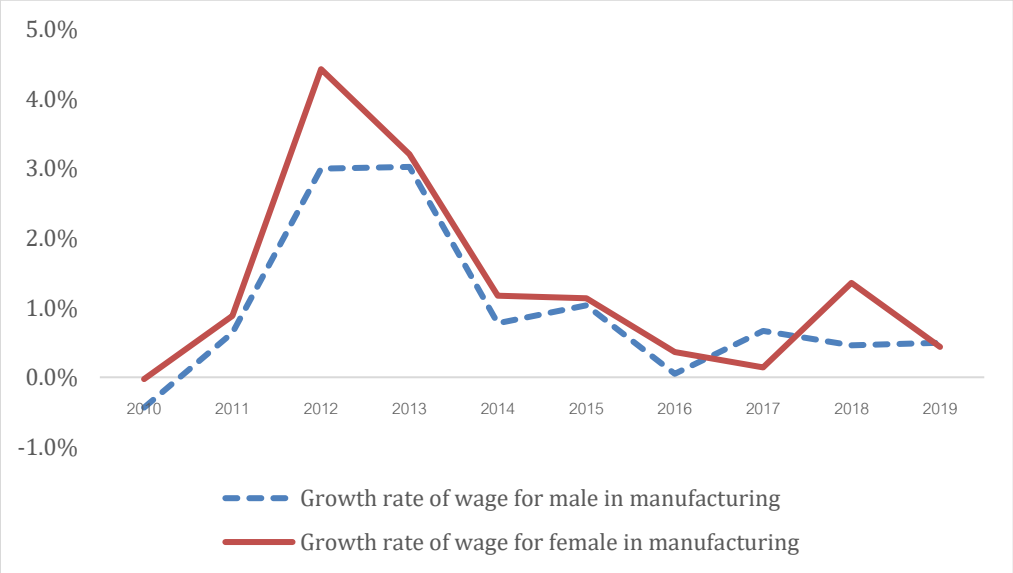
Source: Authors' Calculation from LFS (1985 – 2024)

Figure 9. The stock of robot usage and newly added robot installation in manufacturing from 2010 to 2019



Source: Authors' Calculation from IFR (2010 – 2019)

Figure 10. Growth rate of wage for male and female in manufacturing during 2010-2019



Source: Authors' Calculation from LFS (2010 – 2019)

Table 1. Summary Statistics

	Female			Male		
	1994-1997	1998-2015	2016-2024	1994-1997	1998-2015	2016-2024
Log hourly wage	3.623	3.733	4.165	3.752	3.790	4.109
	(0.942)	(0.860)	(0.723)	(0.873)	(0.808)	(0.674)
Years of schooling	9.381	10.298	11.382	8.589	9.468	10.032
	(5.036)	(5.127)	(4.791)	(4.548)	(4.676)	(4.484)
Brawn	0.641	0.626	0.605	0.641	0.736	0.785
	(0.404)	(0.394)	(0.392)	(0.357)	(0.402)	(0.428)
Brain	0.933	0.873	0.872	0.912	0.830	0.806
	(0.235)	(0.236)	(0.227)	(0.219)	(0.212)	(0.200)
Age	32.839	36.446	39.808	35.120	37.156	40.128
	(10.148)	(10.487)	(10.858)	(10.798)	(11.010)	(11.368)

No. of children	1.207	0.978	0.763	1.254	1.042	0.772
	(1.403)	(1.086)	(0.998)	(1.188)	(1.115)	(1.023)
Marital status (0=Single; 1=Married)	0.568	0.626	0.491	0.703	0.691	0.515
	(0.495)	(0.484)	(0.500)	(0.457)	(0.462)	(0.500)
Urban (0=Rural; 1=Urban)	0.505	0.658	0.603	0.458	0.637	0.576
	(0.500)	(0.474)	(0.489)	(0.498)	(0.481)	(0.494)
Observations	60,211	364,773	134,341	76,807	415,007	154,322

Note: Mean is presented for each variable. Standard errors are in parentheses.

Source: Authors' Calculation from LFS (1994–2024).

Table 2. Return on years of schooling using IV

	(1)	(2)	(3)	(4)	(5)	(6)
		Female			Male	
	1994-1997	1998-2015	2016-2024	1994-1997	1998-2015	2016-2024
Years of schooling	0.0470***	0.000336	0.102***	-0.0169	0.0506***	0.0892***
	(0.016)	(0.005)	(0.012)	(0.034)	(0.006)	(0.018)
Age	0.0549***	0.0335***	0.00521	0.0624***	0.0164***	0.00171
	(0.003)	(0.001)	(0.003)	(0.006)	(0.001)	(0.005)
Age squared	-0.000434***	-0.000231***	0.000162***	-0.000571***	2.67E-05	0.000137*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of children	-0.00157	-0.0275***	-0.0218***	-0.0535***	-0.0132***	-0.00505*
	(0.002)	(0.001)	(0.002)	(0.012)	(0.002)	(0.003)
Marital status	0.0556***	0.0566***	0.0459***	0.105***	0.113***	0.0845***
	(0.007)	(0.003)	(0.003)	(0.007)	(0.002)	(0.007)
Control for industries and occupations	Yes	Yes	Yes	Yes	Yes	Yes
Control for time effects and regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,211	364,773	134,341	76,807	415,007	154,322

Note: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. The Wald F-statistic for IV suggests the instrument is not weak.
Source: Authors' estimates.

Table 3. Return on skills using IV

	(1)	(2)	(3)	(4)	(5)	(6)
		Female			Male	
	1994-1997	1998-2015	2016-2024	1994-1997	1998-2015	2016-2024
Skills	1.668***	0.635***	1.040***	-0.438	1.238***	0.843***
	(0.330)	(0.032)	(0.082)	(1.061)	(0.152)	(0.148)
Age	-0.0105	0.0348***	0.0141***	0.0880**	-0.000683	0.00889**
	(0.023)	(0.001)	(0.003)	(0.041)	(0.005)	(0.004)
Age squared	0.000322	-0.000244***	-1.91E-05	-0.000828*	0.000133***	-4.11E-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of children	0.0416**	-0.0230***	-0.00226	-0.0559***	0.0164**	0.00548
	(0.017)	(0.002)	(0.005)	(0.008)	(0.008)	(0.007)
Marital status	0.0101	0.0526***	0.0316***	0.0774***	0.0482***	0.0501**
	(0.012)	(0.003)	(0.004)	(0.025)	(0.010)	(0.022)
Control for industries	Yes	Yes	Yes	Yes	Yes	Yes
Control for time effects and regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,224	367,159	136,013	76,832	417,959	156,422

Note: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. The Wald F-statistic for IV suggests the instrument is not weak.
Source: Authors' estimates.

Table 4. Return on years of schooling and skills using IV by high-tech and low-tech industry

	(1)	(2)	(3)	(4)
	High-tech		Low-tech	
	Male	Female	Male	Female
Years of schooling				
Skills	-2.807***	1.113***	0.213***	-0.610***
	(0.511)	(0.027)	(0.082)	(0.171)
Age	0.249***	0.0361***	0.0455***	0.0562***
	(0.030)	(0.002)	(0.002)	(0.004)
Age squared	-0.00237***	-0.000191***	-0.000487***	-0.000817***
	(0.000)	(0.000)	(0.000)	(0.000)
No. of children	-0.191***	-0.00660***	-0.0178***	-0.0663***
	(0.024)	(0.002)	(0.003)	(0.008)
Marital status	0.124***	0.0781***	0.0744***	-0.108***
	(0.013)	(0.003)	(0.003)	(0.012)
Control for industries and occupations	Yes	Yes	Yes	Yes
Control for time effects and regional dummies	Yes	Yes	Yes	Yes
Observations	298,500	293,953	263,906	215,141

Note: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. The Wald F-statistic for IV suggests the instrument is not weak.
Source: Authors' estimates.

Table 5. Return on skills using IV by married and unmarried women

	(1)	(2)
	Married women	Unmarried women
Skills	1.718***	0.705***
	(0.12)	(0.04)
Age	0.00192	0.0278***
	(0.00)	(0.00)
Age squared	0.000106***	-0.000195***
	(0.00)	(0.00)
No. of children	0.0222***	-0.0329***
	(0.00)	(0.00)
Control for industries	Yes	Yes
Control for time effects and regional dummies	Yes	Yes
Observations	155,208	80,992

Note: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. The Wald F-statistic for IV suggests the instrument is not weak.
Source: Authors' estimates.

Table 6. Return on brain and brawn skills using pseudo-panel approach

	(1)	(2)	(3)	(4)	(5)	(6)
		Female			Male	
	1994-1997	1998-2015	2016-2024	1994-1997	1998-2015	2016-2024
Brain	0.446	2.205***	1.112***	-0.298	1.062***	0.611***
	(0.385)	(0.140)	(0.195)	(0.342)	(0.168)	(0.206)
Brawn	-0.181	0.0129	-0.465***	-0.281	0.441***	-0.531***
	(0.170)	(0.079)	(0.108)	(0.197)	(0.098)	(0.083)
Age	0.00979	0.00274	0.0108**	0.0372**	-0.00839	0.0126***
	(0.013)	(0.004)	(0.004)	(0.015)	(0.007)	(0.005)
Age squared	0.000243	0.000162***	8.56E-05	-2.45E-05	0.000290***	5.69E-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of children	0.0145	0.0418***	-0.0218	0.0462***	0.0189	0.0223
	(0.015)	(0.013)	(0.030)	(0.017)	(0.014)	(0.036)
Marital status	0.244*	0.362***	0.0358	-0.059	0.582***	-0.126*
	(0.146)	(0.059)	(0.063)	(0.130)	(0.084)	(0.072)
Control for time effects and regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135	755	215	135	755	215

Note: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Source: Authors' estimates.

Table 7. Blinder-Oaxaca Decomposition Results

	(1)	(2)	(3)	(4)	(5)
	1994-1997	1998-2015	2016-2024	2016-2024 High-tech	2016-2024 Low-tech
Total Difference	0.128***	0.0576***	-0.0596***	0.130***	0.0107***
	(0.005)	(0.002)	(0.003)	(0.005)	(0.003)
Unexplained	0.104***	0.176***	0.112***	0.135***	0.135***
	(0.004)	(0.001)	(0.002)	(0.004)	(0.003)
Explained	0.0245***	-0.119***	-0.172***	-0.00493*	-0.125***
	(0.003)	(0.001)	(0.002)	(0.003)	(0.002)
Explained details:					
Brain	-0.0228***	-0.0710***	-0.0915***	0.0146***	-0.0333***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Brawn	-0.00052	-0.0550***	-0.0775***	-0.0120***	-0.0813***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.159***	0.0188***	0.00858***	-0.0281***	-0.00143
	(0.005)	(0.001)	(0.001)	(0.003)	(0.002)
No. of children	-0.00170***	-0.00159***	-0.000126	5.88E-05	-0.000266***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marital status	0.0105***	0.00520***	0.00157***	-0.000214	0.000566***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	137,056	785,118	292,435	60,796	185,755

Note: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

This table presents the gender wage gap accounting for the effect of stock of robots and computer usage. Positive total differences suggest that men have higher average wages than women.

Table 8. Return on skills controlling for stock of robots and computer usage by gender using IV estimation

	(1)	(2)	(3)	(4)
	IV_Women	IV_Men	IV_Women	IV_Men
Years of schooling	0.238***	0.00097	0.150***	0.468***
	(0.022)	(0.008)	(0.018)	(0.018)
Stock of robots	1.27e-05**	6.69e-05***		
	(0.000)	(0.000)		
Computer usage			-0.0129	-0.457***
			(0.013)	(0.034)
Age	-0.0107*	0.0167***	-0.0140*	-0.0703***
	(0.006)	(0.002)	(0.007)	(0.004)
Age squared	0.000547***	-0.000161***	0.000358***	0.00146***
	(0.000)	(0.000)	(0.000)	(0.000)
No. of children	-0.00778**	-0.0102***	-0.0246**	-0.183***
	(0.003)	(0.001)	(0.011)	(0.006)
Marital status	0.158***	0.0603***	0.221***	-0.0927***
	(0.016)	(0.004)	(0.042)	(0.014)
Control for industries and occupations	Yes	Yes	Yes	Yes
Control for time effects and regional dummies	Yes	Yes	Yes	Yes
Observations	58,629	85,980	29,505	66,799

Note: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. The Wald F-statistic for IV suggests the instrument is not weak.

Source: Authors' estimates.

Table 9. Return on skills controlling for stock of robots by gender and skill levels using IV estimation

	(1)	(2)	(3)	(4)	(5)	(6)
		Female			Male	
	Low skill	Middle skill	High skill	Low skill	Middle skill	High skill
Years of schooling	0.484***	0.0147	0.0279	0.0372***	0.00389	0.0241
	(0.092)	(0.011)	(0.047)	(0.009)	(0.014)	(0.036)
Stock of robots	-4.45E-06	7.67e-05***	2.53e-05**	7.78e-05***	6.78e-05***	5.41E-06
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.0260*	0.0189***	0.0309**	0.0118***	0.0197***	0.0301***
	(0.014)	(0.004)	(0.012)	(0.002)	(0.005)	(0.010)
Age squared	0.00101***	-0.000180***	-8.90E-05	-9.04e-05***	-0.000139*	-1.80E-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of children	-0.0669***	-0.00614***	-0.0438***	-0.0128***	0.00203	-0.0126
	(0.015)	(0.002)	(0.010)	(0.002)	(0.003)	(0.008)
Marital status	0.258***	0.0012	-0.0348	0.0702***	0.0241***	0.00792
	(0.052)	(0.009)	(0.033)	(0.004)	(0.007)	(0.021)
Control for time effects and regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,317	23,822	6,490	52,994	24,032	8,954

Note: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. The Wald F-statistic for IV suggests the instrument is not weak.

Source: Authors' estimates.

Table 10. Blinder-Oaxaca Decomposition Results

	(1)	(2)
	2010-2019 (Robot)	2019-2023 (Computer)
Total Difference	0.101***	-0.398***
	(0.003)	(0.004)
Unexplained	0.135***	0.182***
	(0.003)	(0.004)
Explained	-0.0337***	-0.580***
	(0.002)	(0.004)
Explained details:		
Brain	0.0542***	-0.309***
	(0.001)	(0.003)
Brawn	-0.0583***	-0.228***
	(0.001)	(0.003)
Stock of robots	-0.0109***	
	(0.002)	
Computer usage		0.00499***
		(0.001)
Age	0.00295**	0.00647***
	(0.001)	(0.001)
No. of children	-3.22E-06	-0.0292***
	(0.000)	(0.001)
Marital status	-0.00159***	-0.00566***
	(0.000)	(0.000)
Observations	146,952	96,913

Note: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.
This table presents the gender wage gap accounting for the effect of stock of robots and computer usage. Positive total differences suggest that men have higher average wages than women.