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ORIGINAL ARTICLE

Brain over brawn: Job polarisation, structural change, and skill prices

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Abstract

This study investigates the relationship between occupational skills and wages in Thailand using the Labour Force Survey from 1985 to 2020. We quantify the contribution of changes in the skill requirement and highlight the increase in the return on the 'brain' and the decrease in the penalty on 'brawn', which helps explain the wage distribution changes across periods. We further explore the polarisation in the labour market and analyse the changes in the wage distribution by applying the decomposition method proposed by Firpo et al (2009). Our results suggest that wage dispersion increases in the top end over the first two time periods but decreases in the third time period, while it continues to decrease in the lower end of the distribution.

Keywords: decomposition; job tasks; polarisation; RIF-regressions; structural change; wage inequality

JEL Codes: J20; J23; J24; J31

Introduction

A large body of research has examined the increase in wage inequality in developed and developing countries in recent decades. Traditionally, most studies on wage inequality have focused on explanations that relate to changes in returns on education and experience (e.g., Juhn et al 1993; Katz and Murphy 1999). Recently, the role of occupations in wage inequality changes has begun to draw a great deal of attention in developed countries. For example, Autor et al (2006, 2008) document the trend of wage polarisation in the US caused by a decline in the demand for middle-skill workers and provide an explanation based on skill-biased technological change (SBTC). This phenomenon has also been found in Germany (Spitz-Oener 2006), Britain (Goos and Manning 2007), Japan (Ikenaga and Kambayashi 2016), and 16 Western European countries (Goos et al 2014).

Offshoring has also contributed to changes in occupational wage structures in developed countries by replacing domestic workers with low-cost labour in developing countries (Blinder 2009; Firpo et al 2011; Jensen and Kletzer 2010). Automation has increased the demand for skilled and low-skill non-routine jobs (Autor et al 2003; Goos and Manning 2007). Buera et al (2018) use skill-biased structural change to explain the redistribution of industry value-added shares to high-skill-intensive industries associated with the growth in high-skilled labour demand, contributing to the increased skill premium in advanced countries.

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Given their different occupational structures and the impact of offshoring, recent technological progress, which has been driving labour market polarisation in developed countries, should result in different dynamics in developing countries. However, unlike in developed countries, polarisation in developing countries has not attracted much attention. Reijinder and Vries (2017) find that job polarisation is not a phenomenon that occurs only in developed countries; it happens in most major emerging countries, including China, India, Indonesia, and Mexico.

Thailand provides an interesting developing country case study investigating the return on skills and polarisation. Thailand's economic growth has elevated it from a low-income status to that of a high-middle-income country, which has helped many people escape poverty. The real income of Thai citizens increased at an average rate of 4% per year from 1950 to 2014 (Penn World Table database 2017). One of the main factors that explain the increased income is Thailand’s transition from an agricultural economy to a manufacturing and service-oriented economy (Vanitcharearnthum 2019).

This study first explores the relationship between occupational skills (specifically brain and brawn skills) and wages in Thailand. In addition to measuring the return on skill using the relative wage increase for those who are more highly educated, we consider structural transformation over time using brain and brawn job requirements via occupation-industry pairs. Following Autor et al (2003) and Rendall (2013), we use the ordinal ranking of intellectual and physical job requirements by occupation-industry pairs. This enables us to match, using US job requirements, to control for Thailand’s unknown requirements and provide insight into the return on skills over time.

Next, using the decomposition method proposed by Firpo et al (2009, 2011), we further investigate the polarisation in the labour market and analyse the contribution of skill requirements to the wage distribution changes in Thailand. This decomposition method combines the ideas of the DiNardo, Fortin, and Lemieux (DFL) decomposition method (DiNardo et al 1996) with the classic Oaxaca-Blinder (OB) decomposition method (Oaxaca 1973; Blinder 1973) and employs a recentred influence function (RIF) regression to provide the decomposition of any distributional parameter, such as quantiles or Gini coefficients.

We provide new evidence regarding wage polarisation in developing countries, finding that wage inequality increases in the top end of the distribution but decreases in the lower end, similar to developed countries (e.g., Autor et al 2006; Firpo et al 2011). However, this does not persist, only appearing from 1985 to 1995. Furthermore, it is not accompanied by the employment polarisation seen in developed countries, as the major difference in Thailand is its occupational structure. We also highlight changes in return on brain and brawn skills over time; the structural transformation helps explain the faster wage increase for high-skill workers compared to middle-skill workers and the decrease in the gap between lower- and middle-skill workers.

The rest of the paper is organised as follows. Section 2 discusses the related literature, and Section 3 provides the study background. Section 4 describes the data, while Section 5 explains the methodology. Section 6 analyses the results, and Section 7 concludes.

Literature review

An increase in wage inequality has been observed in many developed countries (e.g., Atkinson et al 2011; Autor et al 2008; Lemieux 2006 for the US; Card et al 2013; Dustmann et al 2009; for Germany; Machin 2003 for the UK; Koeniger et al 2007 for the Organisation for Economic Co-operation and Development (OECD) countries; Lise et al 2014 for Japan). The main hypothesis the literature proposes to explain the increase in wage inequality is SBTC (e.g., Acemoglu and Autor 2011; Autor et al 2008; Katz and Autor 1999; Maarek and Moiteaux 2021), which explains the expansion of wage dispersion both between and within

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education groups (Goldin and Katz 2009; Katz and Murphy 1999). Other factors, like the role of skilled workers, changes in institutions, the increase in international trade, and workplace heterogeneity, have been considered as reasons for the increase in wage inequality (Antonczyk et al 2018; Bienwen et al 2017; Card et al 2013; DiNardo et al 1996; Lemieux 2006).

More recently, as studies have suggested that a general increase in wage inequality is not sufficient to describe the recent labour market trends, Autor et al (2003) have introduced the task approach and proposed a nuanced version of SBTC, in which technology can substitute human workforce in routine tasks but not in non-routine tasks, causing the polarisation in the labour market. Goos and Manning (2007) also show evidence of polarising employment in the UK, which supports Autor et al's (2003) hypothesis. Many later studies have shown the pervasiveness of job polarisation in other developed countries (Dustmann et al 2009; Goos et al 2009; Katz and Margo 2013; Park et al 2023).

Job polarisation in the US has been accompanied by wage polarisation, where wages at the bottom and top of the distribution increase faster than those in the middle (Autor et al 2006, 2008). However, although job polarisation and wage inequality occur concurrently, the link between the two is still unknown. Studies have suggested that wage polarisation is the result of the employment decline in middle-skill jobs due to technological progress (Acemoglu and Autor 2011; Autor and Dorn 2013; Cavaglia and Etheridge 2020), indicating occupation is the key empirical channel for the recent changes in wage inequality. Some relevant strands of the literature suggested job polarisation caused by a structural change from manufacturing to services, inducing employment in high- and low-skill occupations and change in relative wages (Autor and Dorn 2013; Bárány and Siegel 2018; Fierro et al 2022). In addition, several models have been developed to explain the phenomenon of job and wage polarisation in advanced economies, such as the agent-based model with heterogeneous workers, heterogenous firms, various labour market institutions, and policies (Bordot and Lorentz 2021; Dawid and Neugart 2021; Fierro et al 2022; Mellacher and Scheuer 2020).

Another aspect of the change in the wage structure through occupations in developed countries lies in the expansion of offshoring opportunities, allowing foreign labour to substitute for domestic workers in some tasks (Blinder 2009; Blinder and Krueger 2013; Jensen and Kletzer 2010). Acemoglu and Autor (2011) suggest that offshorability plays a minor or insignificant role, while Firpo et al (2009) find that offshorability is significant in explaining wage polarisation. Autor (2015) suggest that China's rapid rise in manufacturing has a far-reaching impact on US workers by reducing employment and depressing labour demand. However, for developing countries, including Hungary, Malaysia, the Philippines, Mexico, Pakistan, Sri Lanka, and Thailand, Hanson and Robertson (2008) suggest that China's impact has been relatively small.

While polarisation has become one of the most discussed topics in labour economics in developed countries, it is rarely considered in developing countries, given the difference in occupational distributions, the impact of offshored jobs from developed countries, and the impact of technological progress. There is no evidence of polarisation in developing countries on average, but a few countries, like Indonesia, Mexico, and Brazil, show some evidence of incipient polarisation (Maloney and Molina 2016). Cornfeld and Danieli (2015) finds evidence of wage polarisation in Israel, and Helmy (2015) shows that job polarisation is growing with the expansion of wage disparity in Egypt.

In developing countries, a large share of the labour force is employed in agriculture, while middle-skilled workers occupy only a small proportion. Therefore, as Maloney and Molina (2016) indicate, the potential polarisation dynamics lie in different initial occupational structures and demographics. In addition, the decrease in middle-skill jobs caused by offshorability in developed countries provides more employment opportunities

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in developing countries, which may result in 'de-polarisation' for countries like China. Reijinder and Vries (2017) suggest that while offshoring has contributed to polarisation in developed countries, 'anti-polarisation' (or the opposite effect), is seen in primary offshore destinations like China and Eastern Europe. Furthermore, under globalisation, as the levels of skilled jobs are classified differently in developed and developing countries when jobs are relocated, low-skill jobs in developed countries can be performed by middle-skill workers in developing countries (Goldberg and Pavcnik 2007).

Education is a conventional measure of skill (e.g., Autor et al 2003; Card 2001; Juhn et al 1993). As Ingram and Neumann (2006) suggested, education is a coarse measure of skill that should evolve with economic development and technological change. In developing countries, a structural shift during the period has accompanied the change in job requirements from manual skills (brawn) to intellectual skills (brain) due to technological changes and economic development, playing a significant role in the evolution of wage inequality.

Previous studies of inequality in Thailand have mainly focused on how economic growth, government policies, and education have affected income distribution (e.g., Israngkura 2003; Kilenthong 2016; Krongkaew 1985; Kurita and Kurosaki 2011; Meesook 1979; Motonishi 2006; Paweenawat and McNown 2014; Warr and Isra Sarntisart 2005). As an exception, Lathapipat (2009) suggests that wage polarisation is plausible in Thailand between 1987 and 2006, using education attainment as a proxy for skills. Leckcivilize (2015) provides evidence that the minimum wage has a minimal impact on reducing wage inequality in Thailand. Te Velde and Morrissey (2004) and Tomohara and Yokota (2011) suggest that foreign direct investment increases wage inequality in Thailand, as it has a larger impact on skilled workers than on low-skill workers. Paweenawat (2022) confirmed higher wages and higher skill premiums of workers in the global value chain (GVC)-oriented industries due to the higher demand for skilled workers. Pootrakul (2013) and Vanitcharearnthum (2017) find that although Thailand has had impressive economic growth over the last three decades, income inequality has not improved during that time.

Study background

In this section, we provide an overview of the changes in occupational composition, wage structure, and education in Thailand's labour market between 1985 and 2020 and explore the changes in the employment structure that are relevant to the job polarisation found in developed countries. We draw attention to the development of wage inequality and provide information on how the Thai labour market has changed the value of different levels of occupational skills over the last three decades.

Between 1985 and 2020, the country's industrial structure changed dramatically. Agriculture dropped significantly by around 31%, while the manufacturing, construction, commercial, and service industries have risen accordingly (Figure A1 in the Appendix). In occupational composition, instead of the steep decline in middle-skill employment seen in developed countries, we find a sharp drop in low-skill employment, consistent with the decrease in agriculture, similar to the changes in industrial employment (Figure A2 in Appendix). Middle-skill employment has increased, but high-skill employment has shown relatively little change over time.

Next, we use the categorisation of occupations to define the skills by following Autor (2019). We assign occupations to three skill levels: 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'.[1] Figure 1 illustrates the pattern of changes in three broad skill clusters over time, indicating a decline in low-skill employment (10%), an increase in middle-skill employment (9%), and a

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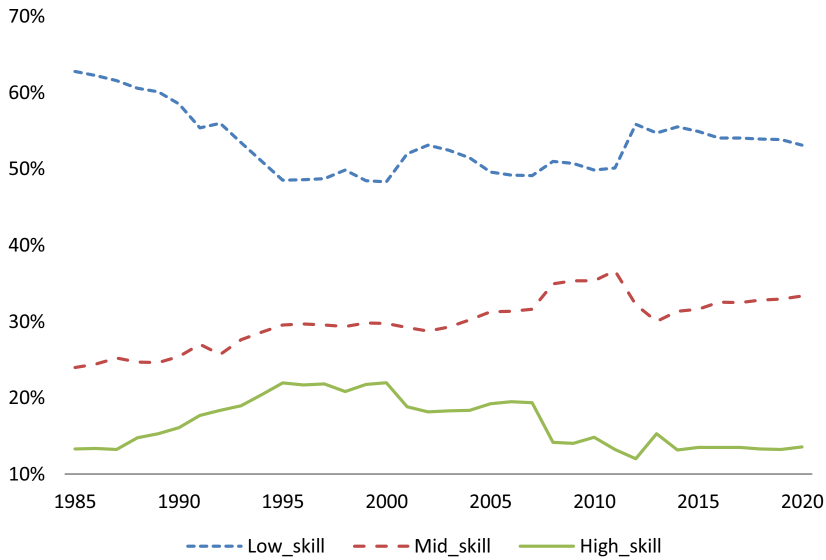

Figure 1. Shares of employment by occupational skills (1985–2020).
Source: Authors' calculations from Thailand's Labour Force Survey (LFS) (1985–2020), conducted by the National Statistical Office. By following Autor et al (2019), the authors assigned occupations to three skill levels: managers, legislators, 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', and then computed the shares of employment by occupational skills over time.

relatively stable pattern for high-skill employment (1%). Therefore, we do not observe job polarisation in Thailand since agriculture has accounted for a large share of the labour force from the beginning, with a low share of middle-skill employment. Instead of job polarisation, the transition in the past three decades has mainly been from agricultural employment to middle-skill employment.

The expansion of education in Thailand has been documented and discussed in previous studies related to income inequality (e.g. Hawley 2004; Knodel 1997; Motonishi 2006; Paweenawat and McNown 2014). Less widely recognised is the change in inequality between different educational and occupational skill groups. In the US, wage polarisation shows that the education premium has strongly increased, with larger wage growth at both ends of the occupational skill distribution (Autor and Dorn 2013). Here, we focus on the progression of wage inequality across educational and skill groups.

Figure 2 shows the growth in the median log of the real hourly wage for the three skill groups. High-skill and low-skill occupations have shown a much faster increase in wages over time than middle-skill occupations. Real wage growth for high-skill and low-skill occupations continued to increase, while real wage growth for middle-skill occupations stagnated until 2011.

Generally, labour employment has transferred from agriculture to manufacturing and service industries, resulting in fewer low-skilled workers and more middle-skilled workers. Unlike the US, with its U-shaped employment shares and wage growth by percentile (Acemoglu and Autor 2011), in Thailand, low-skilled workers experienced the highest wage growth and the largest drop in employment during the last three decades. Thailand has transformed from an agricultural-oriented economy to a manufacturing and service-oriented economy, changing the workforce composition and the wage structure of the Thai labour market. The need for low-skilled workers in the agriculture sector has been replaced by the demand for high-skilled workers in the manufacturing sector. This is especially so in the GVCs-oriented industries, where the strong demand for high-skill

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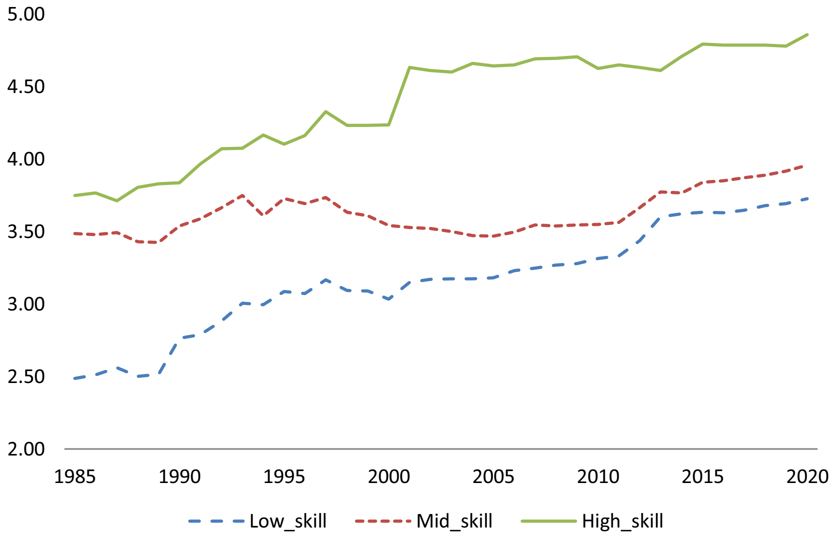

Figure 2. Real log hourly wage by occupational skills (1985–2020).
Source: Authors' calculations from Thailand's Labour Force Survey (1985–2020), conducted by the National Statistical Office. By following **Autor et al (2019), the authors assigned occupations to three skill levels: managers, legislators, 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'; and then computed the hourly wage by occupational skills over time.

workers generates a high wage premium for this group of workers (Paweenawat 2022). Even though high-skilled workers earn higher wages than middle-skilled workers, and those with middle-skills earn higher wages than low-skilled workers (Wasi et al 2019), Figure 2 reveals that the wage gap between high-skilled and middle-skilled workers has expanded while the gap between middle-skilled and low-skilled workers has contracted.

A possible explanation is that the increase in education has not provided an adequate number of high-skilled workers, indicating a quality mismatch in the Thai labour market (Satimanon 2017), while improvement in technology has increased the demand for more high-skilled workers (Tinbergin 1974, 1975; Acemoglu and Autor 2011) causing the change in between-group wage inequality. Lathapipat and Chucherd (2013) suggest that despite the increase in a more highly educated workforce in Thailand in the past two decades, the quality of education is low. Paweenawat and Vechbanyongratana (2015) found that an overeducation incidence in the group of Thai university graduates leads to wage penalties, especially for young workers.

Rendall (2013) presents a breakdown of workers in Thailand, the US, Brazil, Mexico, and India in 1990 and 2005 using three levels of broad brain and brawn job categories. Thailand has added the most in the medium-brain levels of the occupation-industry pairs but was relatively stagnant in the addition of more high-brain occupations, consistent with our findings. Moreover, the magnitude is the largest among the five countries, suggesting that Thailand has experienced a large drop in brawn demand and an increase in brain demand.

Non-routine tasks performed by high-skilled workers, such as more analytical work, and by low-skilled workers, like non-routine manual work, cannot be supplemented by machines, increasing their demand (Acemoglu and Autor, 2011). However, for low-skilled workers, the situation in Thailand is quite different. Unlike developed countries, low-skill employment has historically dominated the labour market, as agriculture accounts for the largest share of employment. The economic development during the last three decades has moved labourers from agriculture to other industries. Up to one million people per year

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transferred from agriculture to urban occupations, and real per capita income doubled (Phongpaichit and Baker 2008). Thailand has changed from a low-income to an upper-income country (World Bank 2023). Wages at the low end of the wage distribution have increased substantially over time due to labour migration from rural to urban areas (Lathapipat 2009). In addition, the wage growth of low-skilled workers may be associated with a rise in minimum wage in the country over time. Thailand has started to enact a minimum wage policy in the labour market since 1973, and this policy may promote an increase in the wage of workers with primary education (Samart 2020).

Note that as we do not observe much change in the share of high-workers, and the share of low-skilled workers is relatively stable after 1995 (Figure 1), job polarisation does not occur in Thailand. Meanwhile, low-skill and high-skill wages have increased over time, accompanied by relatively stable wages for middle-skilled workers (Figure 2), indicating wage polarisation. This study, therefore, provides empirical evidence only regarding wage polarisation.

Ideally, our goal is to estimate wage distribution changes using a dataset containing detailed task content of occupations and skill requirements for jobs with large sample sizes. However, it is difficult in developing countries to find job task requirements like those available from the Dictionaries of Occupational Titles (DOT) or O*NET from the US Department of Labour. Considering the remarkable transformation in Thailand, returns on different skills (brain and brawn) are significant in explaining wage growth over time. Brawn is important in the early stage. However, along with development, the focus has gradually shifted to the brain. These trends are seen in skill prices over time.

Therefore, we use decomposition analysis to investigate the changes in wage inequality over time, quantifying the contribution of brawn and brain by matching the job requirements from the DOT. By including the skill requirements of both occupations and industries in the estimation, we provide insight into the transformation of the labour market over time.

Data

The data utilised in this study are from Thailand's Labour Force Survey (LFS) from 1985 to 2020, conducted by the National Statistical Office (NSO). We employ the third quarter of the year to avoid the seasonal migration problem of Thai agricultural workers (Sussangkarn and Chalamwong 1996; Warunsiri and McNown 2010). The data were divided into three periods for the analysis based on the country's economic situation. The first period was from 1985 to 1995 when the country experienced a fast growth period preceding the financial crisis. During that time, Thailand's economy was among the fastest-expanding economies globally. The second period, from 1996 to 2006, includes the 1997 Asian financial crisis, the deep economic recession of 1998, and the gradual recovery in the 2000s. There was stagnant wage growth during this period, especially for the high end of the wage distribution. The final period is 2007 to 2020, covering several economic events, including the global financial crisis in 2008, the Thailand floods in 2011, the Eurozone crisis in 2012, and the COVID-19 pandemic in 2020, which show a comparatively lesser impact on wage growth when compared to the Asian financial crisis in 1997. This final period shows fast growth for the low end and a declining trend, moving to the higher end of the distribution.

The data includes individual worker information regarding wages, weekly working hours, occupation, industry, age, gender, and education. The wage measure used in this study is the log of the hourly wage.[2] As the LFS does not directly provide hourly wages, they are calculated by dividing weekly wages by workers' working hours. The sample is restricted to workers between the ages of 15 and 60.[3] Individuals are assigned to three

Table 1. Summary statistics for Labour Force Survey from 1985 to 2020

Descriptive Statistics	1985–1995	1996–2006	2007–2020
Log hourly wage	3.437	3.690	3.933
	(0.940)	(0.870)	(0.769)
Gender (0 = male; 1 = female)	0.439	0.458	0.463
	(0.496)	(0.498)	(0.499)
Age	32.746	35.394	38.146
	(10.645)	(10.479)	(10.997)
Number of children	1.379	1.093	0.944
	(1.357)	(1.126)	(1.092)
Married (0 = unmarried; 1 = married)	0.600	0.662	0.660
	(0.490)	(0.473)	(0.474)
Year of schooling	8.512	9.515	10.330
	(4.744)	(4.850)	(4.885)
Education dummies:			
Primary level	0.513	0.424	0.344
	(0.500)	(0.494)	(0.475)
Secondary level	0.339	0.364	0.398
	(0.473)	(0.481)	(0.489)
University level	0.149	0.213	0.258
	(0.352)	(0.409)	(0.420)
Observations	194,267	433,196	657,676

Source: Authors' calculations.

educational groups. The primary level includes those with no, some, or completed primary level education; the secondary level includes those with some or completed secondary level education; the university level includes those with some or completed university level education or higher. The years of schooling range from 0 (with no education) to 23 (with a PhD degree). The key set of covariates includes years of schooling, age, age squared, occupational dummies, marital status, number of children, and five regional dummies. Table 1 reports the descriptive statistics (the means and standard deviations of the listed variables) in three periods, where we obtained 194,267, 433,196, and 675,676 observations, respectively. While the share of women in the sample is around 44–46%, that of men is about 54–56%. Wages and education have increased while the number of children in employment has decreased over time.

In the empirical analysis, brain and brawn skills are constructed as a more efficient indicator of skills for estimation. Following Rendall (2013), we use the job requirements from the DOT 1991 to map to the Thai data. This method requires the strong assumption that occupations and industries in Thailand require the same skills as those in the US. To solve this problem, Autor et al (2003) normalise the skills to percentiles for other countries, assuming that skill requirement ranks for occupations and industries in the US match the requirement ranks in other countries on an ordinal scale.[4] For example, technicians require more brain work than agricultural workers in all countries.

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By controlling the skill levels for both occupations and industries, we provide additional insights into the structural changes in the labour market. For example, clerks in the construction and service industries may have similar skills, but the average skill requirements for the two industries are different. The skill requirements for each industry and occupation are provided on a scale of 0 to 1 for the 1991 DOT, which supports the consistency of ordinal ranks over time.

According to Rendall (2017), the brain is computed using the average standardised general educational development and specific vocational training, and the brawn is computed using the average between physical strength requirements and environmental conditions.[5] The element composition for the brain includes reasoning and mathematical skills, language proficiency, targeted vocational training, overall intelligence, verbal capabilities, clerical aptitude, and auditory skills. Brawn includes climbing and balancing, stooping/kneeling/crouching/crawling, strength demands for indoor and outdoor tasks, and exposure to the environment.

Figures A3 and A4 show the combinations of skill intensity related to brawn and brain, respectively, by occupation and industry. In Figure A3, the requirements for brawn skills are different for the same occupation in each industry. For example, elementary occupations in the finance and business service industries require less brawn than elementary occupations in the agriculture and hunting industries. While Figure A3 shows a clear pattern for brawn skills, we could not see such a clear pattern for brain skills in Figure A4, which, for a given occupation, is relatively constant across industries. Note that for each industry, there is also wide dispersion among occupations for brawn and brain. For example, elementary and agricultural occupations have a higher need for brawn than other occupations, while professionals, technicians, and managers have a higher need for brains.

Methodology

We first estimate the return on brain and brawn skills using the Mincer wage regression:

$$lnw_i = X_i\delta + S_i\beta + \varepsilon_i \tag{1}$$

Where $\boldsymbol{w_i}$ is the hourly wage of individual 1, $\boldsymbol{X_i}$ represents the individual's characteristics, including age, age square, years of schooling, number of children, marital status, time effects, and five regional dummies. $\boldsymbol{S_i}$ indicates the skill requirements, two distinct (brawn and brain), continuous variables measuring the brain and brawn skill content of jobs. $\boldsymbol{\beta}$ represents the relationship between occupational skills and wages.

Next, we apply the Firpo, Fortin, and Lemieux (FFL) decomposition approach introduced by Firpo et al (2009) to analyse the wage rate changes. As noted by Firpo et al (2018), the standard OB decomposition is limited to the sensitivity of the choice of the base group (Oaxaca and Ransom 1999) and the linearity assumption of the conditional expectations (Barsky et al 2002).

The FFL method was based on the standard OB decomposition method (Blinder 1973; Oaxaca 1973) and the DFL decomposition method (DiNardo et al 1996), using the RIF of Y as the dependent variable. We focus on the differences in wage distributions between two groups using propensity scores. As Firpo et al (2009, 2011) suggested, the main advantage of RIF regression is that it enables us to perform a linear approximation of a highly non-linear function, including wage quantiles, the variance in log wage, and the Gini coefficient.

The decomposition process consists of two steps (Firpo et al 2011, 2018): first, like DiNardo et al (1996), the distributional statistic of interest is decomposed into wage structure and composition components utilising a reweighting method. Second, like the standard OB decomposition, we divide the wage structure and composition component into each covariate's contribution using RIF.

The FFL decomposition separates the total change (Δ_O^ν) into a composition effect (Δ_X^ν) and a wage structure effect (Δ_S^ν):

$$\Delta_O^\nu = \nu\left(F_{Y_1|T=1}\right) - \nu\left(F_{Y_0|T=1}\right) + \nu\left(F_{Y_0|T=1}\right) - \nu\left(F_{Y_0|T=0}\right) \quad (2)$$

$$\Delta_O^\nu = \qquad \Delta_S^\nu \qquad + \qquad \Delta_X^\nu \quad (3)$$

where $\boldsymbol{\nu}\left(\mathbf{F}_{\mathbf{Y}_1|\mathbf{T}=1}\right)$ is the distributional statistic that employers observe in period T = 1 paid under the wage structure Y of period 1.

By replacing Y with the RIF (y; $\boldsymbol{\nu}$), we can compute the influence function for other distributional statistics (Firpo et al 2009); our interest is in the wage quantiles. For the $\boldsymbol{\tau}$th quantile, the influence function is:

$$IF\left(y; q_\tau\right) = \{\tau - 1(y \leq q_\tau)\}/f_Y\left(q_\tau\right) \quad (4)$$

where $\boldsymbol{q_\tau}$ is the $\boldsymbol{\tau}$th quantile of the F distribution, equal to $\inf\{\boldsymbol{y}|\boldsymbol{F}(\boldsymbol{y}) \geq \boldsymbol{\tau}\}$.

The RIF of the $\boldsymbol{\tau}$th quantile:

$$RIF\left(y; q_\tau\right) = q_\tau + IF\left(y; q_\tau\right) \quad (5)$$

Applying the law of iterated expectations to the distributional statistics, we can determine the conditional expectations of the RIF regressions, capturing the between and within effects of the explanatory variables (Firpo et al 2009, 2011).

Results

Return on skills (Brain vs Brawn)

We first estimate the relative job requirements using occupation-industry pairs by intellectual (brain) and physical (brawn) skills, considering the function of structural labour demand, which has a significant effect on wage distribution.

Table 2 shows the results for skills based on equation (1) for three time periods. The return on the brain is positive, indicating that higher brain requirements lead to higher wages, while the coefficients for brawn are negative, indicating that higher brawn requirements lead to lower wages. The return on the brain increased over the three time periods, and the penalty for brawn decreased over time. In addition, the magnitude of the positive impact of years of schooling declined over time.[6] Figure 3 further provides the coefficients of the wage regression for brain and brawn by year.[7] While both the coefficients present an upward trend, the brain shows a steeper pattern, indicating a faster increase in return on intellectual skills.

In addition, in Table 3, we show the estimates of the wage regression by gender.[8] The return on the brain for females is larger than that for males, while the penalty for brawn for females is smaller than that for males, indicating that the structural shift changes from brawn skills to brain skills benefit women more in terms of occupational matching and returns.[9] Table 4 presents the results by residence area.[10] The return on the brain in urban areas is higher than that in rural areas, indicating a higher demand for skilled labour in urban areas, which correlates with the labour migration from urban to rural and the decrease in the lower-end gap throughout the periods mentioned earlier.

Next, to check the return on skills at different wage quantiles, the RIF regression coefficients for the 90$^{\text{th}}$, 50$^{\text{th}}$, and 10$^{\text{th}}$ quantiles in 1985 to 1995, 1996 to 2006, and 2007 to 2020 are presented in Table 5. The effect of brawn and brain changes at different quantiles of the wage distribution. For example, brawn tends to affect the 10th quantile more than the higher wage quantiles, while the brain has a larger impact on the 90th quantile than on

Table 2. The results of wage regression on brawn and brain

	(1) 1985–1995	(2) 1996–2006	(3) 2007–2020
Brawn	−0.397***	−0.249***	−0.110***
	(0.004)	(0.003)	(0.002)
Brain	0.159***	0.572***	0.896***
	(0.007)	(0.005)	(0.004)
Age	0.0611***	0.0291***	0.00201***
	(0.001)	(0.001)	(0.000)
Age square	−0.000440***	−3.03e-05***	0.000210***
	0.000	0.000	(0.000)
Year of schooling	0.109***	0.0958***	0.0718***
	0.000	0.000	(0.000)
No. of children	−0.0179***	−0.00279***	−0.0195***
	(0.001)	(0.001)	(0.001)
Marital status	0.167***	0.117***	0.0755***
	(0.003)	(0.002)	(0.001)
Control for regions	Yes	Yes	Yes
Constant	1.203***	1.657***	2.308***
	(0.015)	(0.010)	(0.009)
Observations	194,267	433,196	657,676
R-squared	0.638	0.625	0.557

Robust standard errors in parentheses
***p < .01,
**p < .05,
*p < .1.
Source: Authors' calculations.

the lower wage quantiles. Education has a larger positive impact on the 90th and 50th quantiles than on the 10th quantile. Over time, education's impact becomes smaller for the 50th quantile. Consistent with our expectations, brawn skill has a larger effect on the 10th quantile than on others, while the brain has a larger effect on the 90th quantile. The direction of the effect also changes in different quantiles.

Decomposition results

Table 6 shows the overall change from 1985 to 2020. The inequality at the top end of the distribution (the 90–50 gap) increased in the first two time periods and decreased in the third period. By contrast, the 50–10 gap declined in all time periods. A similar pattern was found by Autor et al (2006), where the wage dispersion increases in the top end but decreases in the lower end of the distribution for the US. Distinctively, we observe a decline in the 90–50 gap from 2007 to 2020.

The results of return on skills support the decomposition results that wage dispersion increases in the top end, as the return to the brain increased in the first two time periods,

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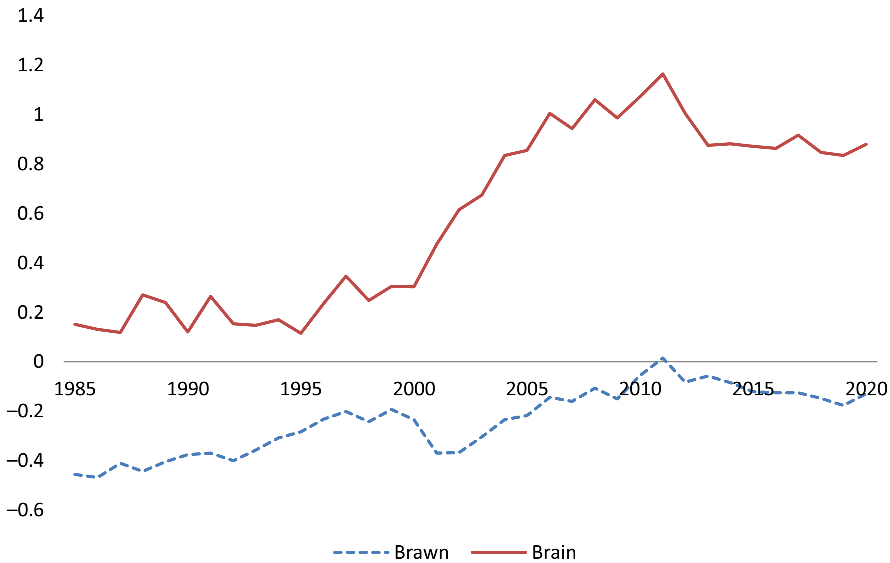

Figure 3. The return on brawn and brain (coefficients) (1985–2020).
Note. All coefficients are significant at 1%, except 2011 is significant at 10%.
Source: Authors' calculations from Thailand's Labour Force Survey (1985–2020), conducted by the National Statistical Office. Following Autor et al (2003) and Rendall (2013), the authors use the ordinal ranking of intellectual and physical job requirements by occupation-industry pairs and provide insight into the return on brain and brawn skills over time. The figure presents the coefficients obtained from Mincer wage regression in estimating returns to skills.

considering the top end related to higher brain skill. In contrast, it decreases at the lower end of the distribution, which relates to higher brawn skill, as the penalty for brawn has declined.

While composition effects account for a small portion of the changes in inequality, the wage structure effect captures the major part of the wage distribution changes (also shown in Figure 4). It is clear that the wage structure effects reduce inequality for the low end (50–10) and increase inequality for the high end (90–50) from 1985 to 1995, while it reduces wage inequality for both the low and high ends during 2007 to 2020. Consistent with Firpo et al (2011), the contribution of the wage structure effect explains the wage polarisation.

The contribution of the covariates suggests that both brawn and brain make a large contribution to the changes in the 90–50 gap and 50–10 gap. Figures 5 and 6 report the detailed decomposition of the composition and wage structure effects for education, brawn, and brain. The wage structure effects linked to each factor play a significant role in the overall change in wage distribution.

A U-shaped change in the wage distribution is found in the first period, indicating that the lower and higher quantiles increase faster than the middle ones, polarising wages. Ikemoto and Uehara (2000) suggest that during the latter part of the 1980s and the early 1990s, as the predominant industry was transformed from export-focused labour-intensive manufacturing to the financial sector, the wages of high-skill workers increased rapidly because supply lagged far behind demand. However, the wages of plant workers could not rise to the same extent as those of skilled workers due to the surplus in the labour supply. In the early 1990s, the wages of agricultural labour started to rise as urban industries absorbed the labour.

The changes in the second period are positive for the lower end and negative for the higher end, with a slower pace compared to the first period. From 1996 to 2006, the

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Table 3. The results of wage regression on brawn and brain by gender

	Male			Female		
	(1)	(2)	(3)	(1)	(2)	(3)
	1985–1995	1996–2006	2007–2020	1985–1995	1996–2006	2007–2020
Brawn	−0.380***	−0.274***	−0.177***	−0.363***	−0.242***	−0.0845***
	(0.006)	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)
Brain	−0.0349***	0.420***	0.772***	0.536***	0.803***	1.036***
	(0.010)	(0.007)	(0.005)	(0.012)	(0.007)	(0.006)
Age	0.0631***	0.0277***	0.00046	0.0599***	0.0347***	0.00842***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age square	−0.000455***	−6.78E-06	0.000217***	−0.000473***	−0.000129***	0.000142***
	0.000	0.000	(0.000)	0.000	0.000	(0.000)
Year of schooling	0.108***	0.0962***	0.0687***	0.107***	0.0929***	0.0749***
	0.000	0.000	(0.000)	(0.001)	0.000	(0.000)
No. of children	−0.0208***	−0.00581***	−0.0163***	−0.0129***	−0.000266	−0.0242***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Marital status	0.135***	0.120***	0.0903***	0.131***	0.0876***	0.0638***
	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
Control for regions	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.449***	1.895***	2.584***	0.839***	1.342***	1.945***
	(0.021)	(0.014)	(0.011)	(0.021)	(0.014)	(0.013)
Observations	108,951	234,653	353,248	85,316	198,543	304,428
R-squared	0.598	0.593	0.523	0.695	0.679	0.61

Robust standard errors in parentheses
***$p < .01$,
**$p < .05$,
*$p < .1$.
Source: Authors' calculations.

magnitude of the total change dropped significantly compared with the first period, corresponding to the impact of the financial crisis, which stagnated wage growth, especially for the higher quantiles.

The results for the first two time periods are consistent with those of Lathapipat (2009). Using the decomposition approach proposed by Lemieux (2006), Lathapipat (2009) found wage polarisation in Thailand from 1987 to 2006, suggesting the SBTC hypothesis is plausible for Thailand. In addition, the large-scale labour migration from rural areas to urban areas by workers attracted by higher wages also explains the decline in the 50–10 gap over time.

In the third time period, the total change shows a declining pattern across quantiles, indicating a decrease in wage inequality. Despite the political coup, floods, and global financial crisis, Thailand's economy has gradually recovered. According to the Asian Development Bank Institute (ADBI) (2019), due to successful policies that facilitated the expansion of financial services to the lower end of the income distribution with enhanced

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Table 4. The results of wage regression on brawn and brain by residence area

	Urban			Rural		
	(1)	(2)	(3)	(1)	(2)	(3)
	1985–1995	1996–2006	2007–2020	1985–1995	1996–2006	2007–2020
Brawn	−0.161***	−0.207***	−0.0811***	−0.426***	−0.260***	−0.137***
	(0.009)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)
Brain	0.489***	0.678***	1.001***	−0.0166	0.459***	0.742***
	(0.011)	(0.007)	(0.005)	(0.011)	(0.008)	(0.007)
Age	0.0691***	0.0277***	−0.000573	0.0562***	0.0358***	0.00778***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age square	−0.000463***	4.12e-05***	0.000278***	−0.000464***	−0.000215***	7.63e-05***
	0.000	0.000	(0.000)	0.000	0.000	(0.000)
Year of schooling	0.101***	0.0931***	0.0727***	0.113***	0.0936***	0.0653***
	0.000	0.000	(0.000)	(0.001)	0.000	(0.000)
No. of children	−0.0299***	−0.00621***	−0.0191***	−0.0104***	−0.00236**	−0.0195***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Marital status	0.193***	0.132***	0.0936***	0.124***	0.0890***	0.0517***
	(0.004)	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)
Control for regions	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.634***	1.522***	2.163***	1.493***	1.596***	2.296***
	(0.021)	(0.013)	(0.011)	(0.021)	(0.016)	(0.014)
Observations	104,984	265,758	381,929	89,283	167,438	230,564
R-squared	0.653	0.649	0.597	0.608	0.538	0.449

Robust standard errors in parentheses
***p < .01,
**p < .05,
*p < .1.
Source: Authors' calculations.

geographic coverage (IMF 2016), financial deepening, measured as the banking and stock market sector's relative share in the economy, helped moderate inequality in several Asian countries, including Thailand.

While government educational policies, for example, compulsory education reform in 1978 and 1999, have successfully helped lower wage inequality, overall results indicated that governments need to give more attention to the quality of education. The increase in education level has yet to provide the labour market with an adequate number of high-skill workers. Therefore, strengthening workers' skills and promoting innovation has been one of the most critical parts of a country's development strategy, especially fostering better conditions for high-quality education. In the high brain demand era, quality education can help enhance and develop workers' comparative advantages in the labour market (Pitt et al 2010; Rendall 2013). Vocational Education and Training that provides workers with

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Table 5. RIF regression estimates on wage

	1985–1995			1996–2006			2007–2020		
	90	50	10	90	50	10	90	50	10
Age	−0.0395***	0.0924***	0.106***	−0.0799***	0.0684***	0.0468***	−0.119***	0.0276***	0.0262***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Age square	0.0011***	−0.0009***	−0.0013***	0.0017***	−0.0006***	−0.0006***	0.0022***	−0.0002***	−0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year of schooling	0.114***	0.135***	0.0391***	0.104***	0.106***	0.0454***	0.118***	0.0565***	0.0385***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
No. of children	0.0352***	−0.0239***	−0.0836***	0.0231***	−0.0127***	−0.0376***	−0.0206***	−0.0116***	−0.0283***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Marital status	0.0952***	0.167***	0.236***	0.133***	0.0844***	0.124***	0.174***	0.0405***	0.0607***
	(0.006)	(0.005)	(0.007)	(0.004)	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)
Brawn	0.124***	−0.496***	−0.846***	0.0833***	−0.265***	−0.615***	0.209***	−0.101***	−0.339***
	(0.006)	(0.006)	(0.013)	(0.004)	(0.004)	(0.007)	(0.004)	(0.003)	(0.005)
Brain	0.754***	−0.0353***	−0.367***	1.020***	0.588***	−0.291***	2.014***	0.678***	0.0102
	(0.015)	(0.013)	(0.016)	(0.010)	(0.008)	(0.009)	(0.012)	(0.005)	(0.007)
Control for regions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	194,267	194,267	194,267	433,196	433,196	433,196	612,493	612,493	612,493

Robust standard errors in parentheses
***$p < .01$,
**$p < .05$,
*$p < .1$.
Source: Authors' calculations.

Table 6. The decomposition results

	90-50			50-10		
	1985–1995	1996–2006	2007–2020	1985–1995	1996–2006	2007–2020
Total change	0.195***	0.0349***	−0.951***	−0.212***	−0.0885***	−0.527***
	(0.017)	(0.011)	(0.009)	(0.016)	(0.009)	(0.006)
Composition	−0.0645***	−0.0898***	0.326***	0.107***	0.189***	0.117***
	(0.011)	(0.006)	(0.007)	(0.011)	(0.006)	(0.005)
Wage structure	0.316***	−0.016	−0.873***	−0.391***	−0.112***	−0.489***
	(0.018)	(0.013)	(0.009)	(0.017)	(0.009)	(0.005)
Specification error	−0.0562***	0.141***	−0.404***	0.0713***	−0.165***	−0.156***
	(0.013)	(0.009)	(0.008)	(0.013)	(0.006)	(0.005)
Observations	45,351	83,331	150,375	45,351	83,331	150,375

Robust standard errors in parentheses
***$p < .01$,
**$p < .05$,
*$p < .1$.
Source: Authors' calculations.

skills and technical knowledge leading to higher payments and better career development is also recommended.

Disaggregation results

While the basic results reflect the changes in general behaviour, the findings may be affected by changes in the composition of the labour market that are not adequately controlled. Therefore, we disaggregate the estimates by subgroups to capture the differences in gender, residence area, birth cohorts, and age groups.

Table 7 shows the decomposition results for the disaggregated data. The groups of men and women show the same pattern of changes for the 90–50 and 50–10 gap, as seen in the overall results. The magnitude of change for the top end (90–50) of the distribution is higher for men than women in the first period, while it is lower for men than women for the lower end (50–10) across all time periods. The gender wage gap has diminished in recent decades due to advancements in women's education (Nakavachara 2010; Paweenawat and Liao 2022). In addition, the structural transformation changes benefit women more through occupational matching and returns. Governments should further attract firms that provide a better environment regarding equal opportunities for both men and women.

The results of the separate decomposition for urban and rural residents show that for the urban area, the pattern of changes for the 90–50 gap and 50–10 gap is the same as that for the overall sample, where the 90–50 gap increases in the first two periods and the 50–10 gap decreases for all periods. However, for rural areas, the results for the second period (1996 to 2006) are the opposite for urban areas, as the 90–50 gap decreases and the 50–10 gap increases. During the financial crisis, rural areas were hit indirectly by reduced government spending and the lost opportunity of working in urban areas. After the crisis, the rural sector absorbed those who lost jobs in urban areas (Ikemoto and Uehara 2000).

The decomposition results disaggregated by birth cohorts show that for the older cohort, the 90–50 gap increases for all time periods, while it begins to decrease for the

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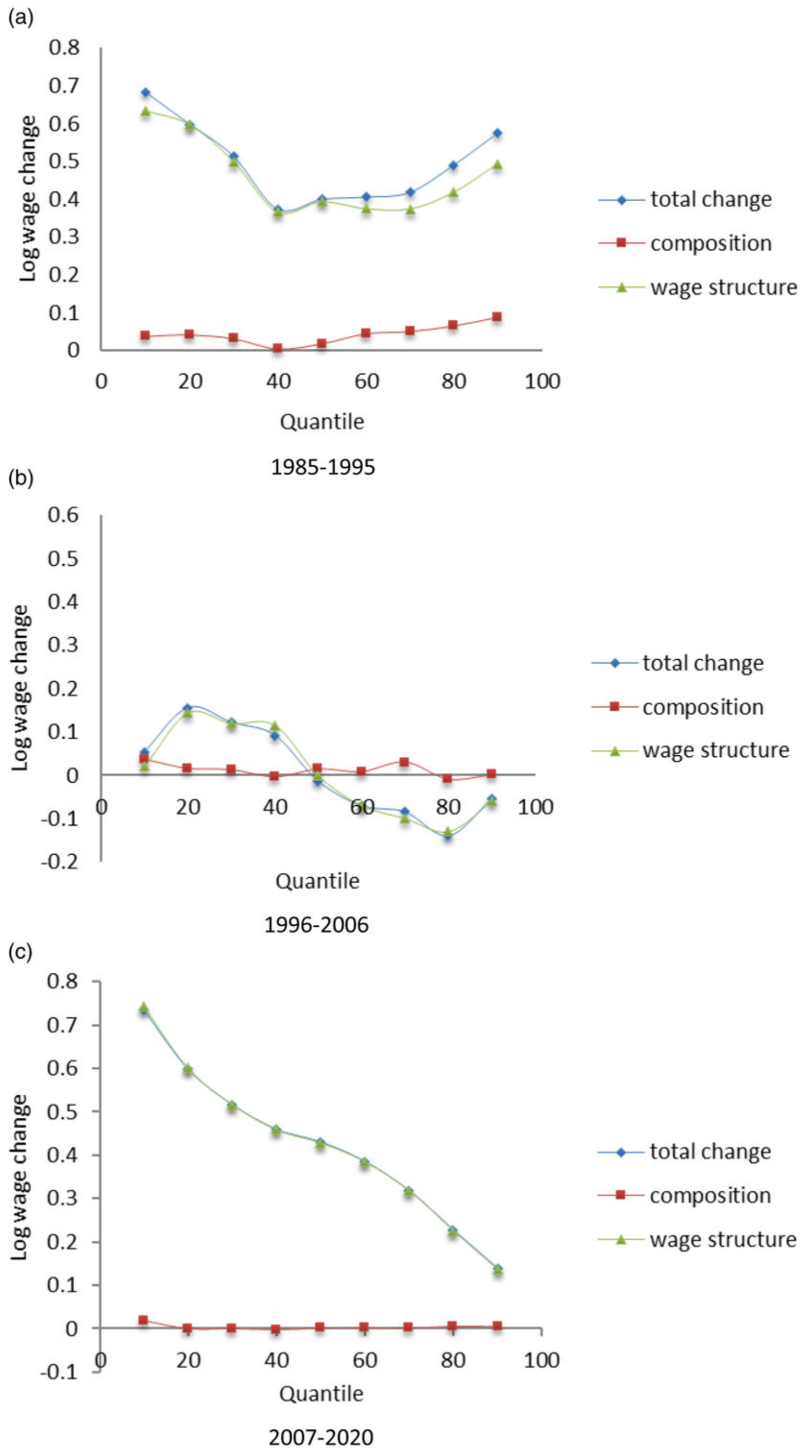

Figure 4. The decomposition of total change into composition and wage structure effect.
Source: Thailand's Labour Force Survey (1985–2020), National Statistical Office.

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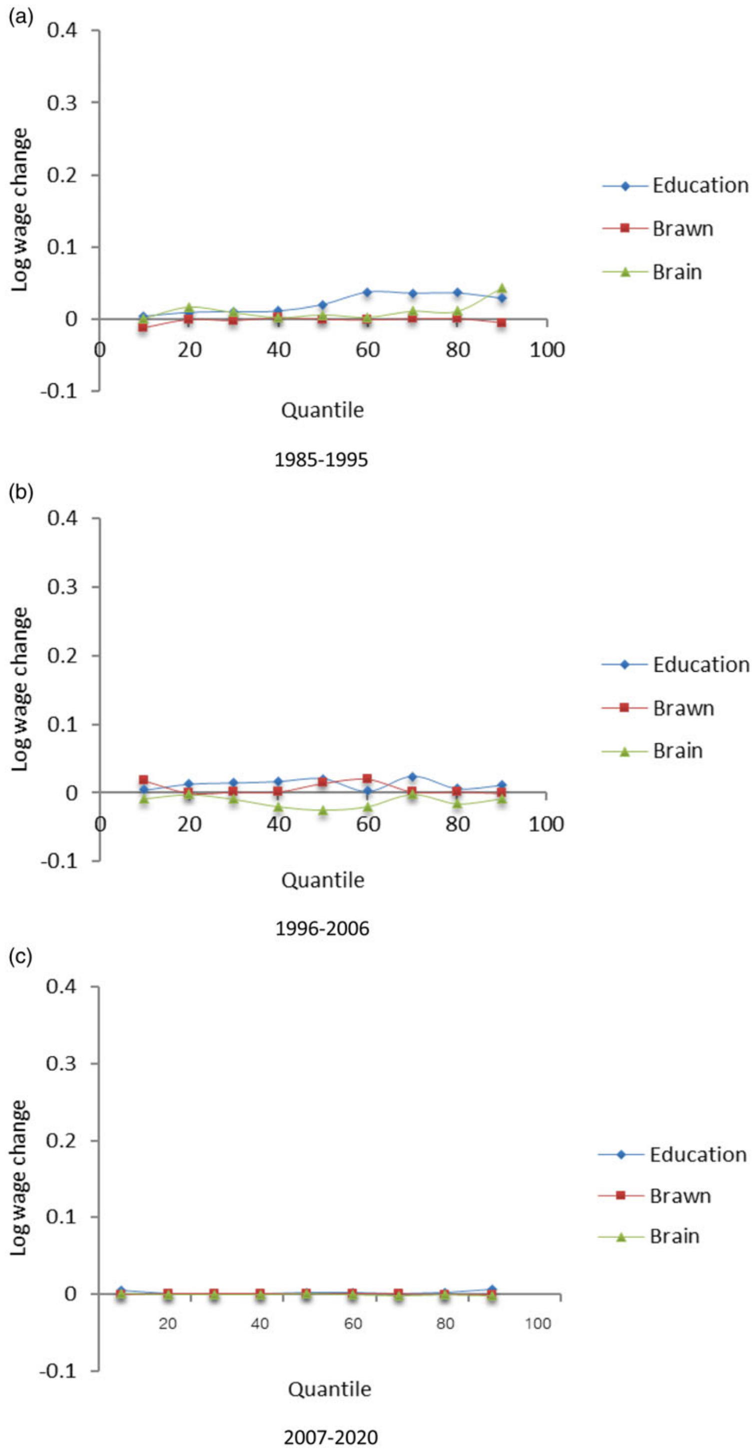

Figure 5. Detailed decomposition for composition effect.
Source: Thailand's Labour Force Survey (1985–2020), National Statistical Office.

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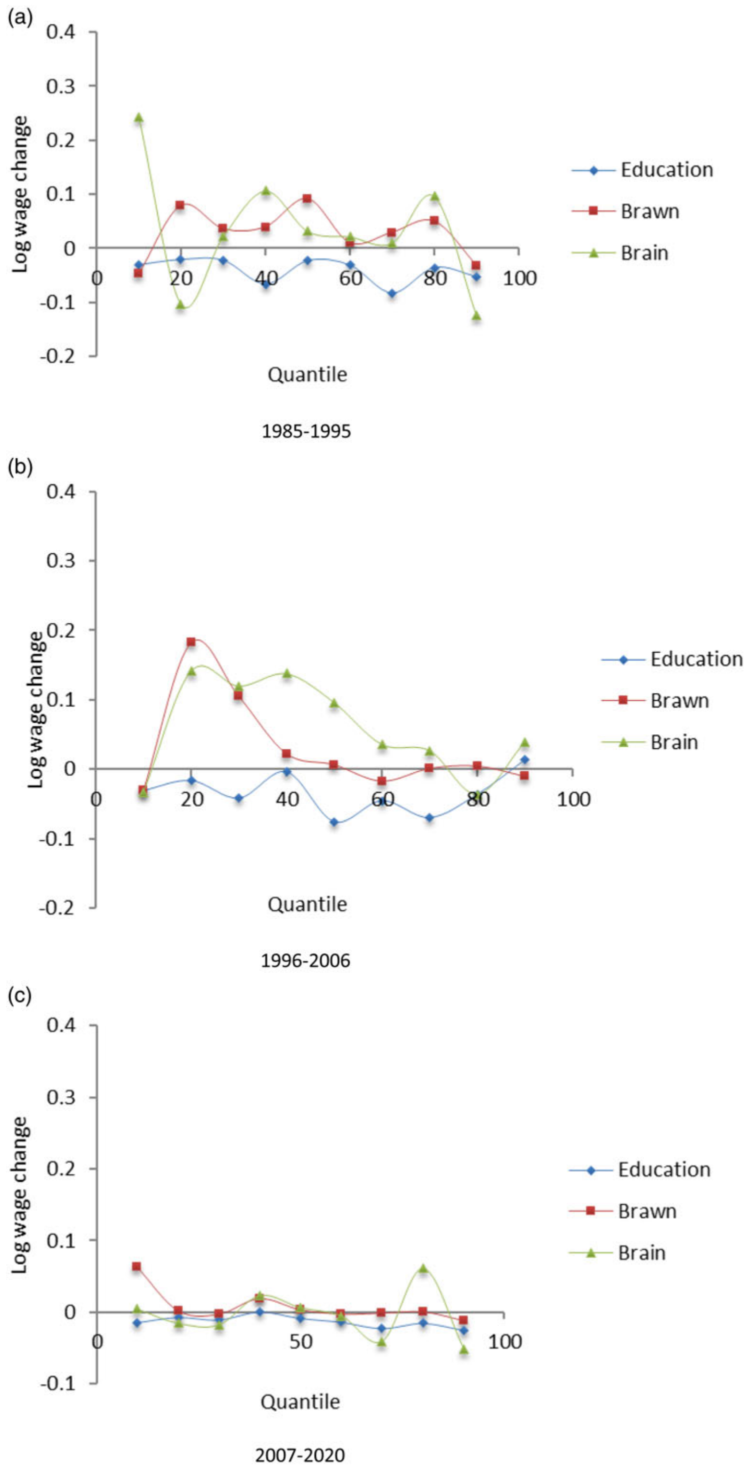

Figure 6. Detailed decomposition for wage structure effect.
Source: Thailand's Labour Force Survey (1985–2020), National Statistical Office.

Table 7. Disaggregation results

	90-50			50-10		
	1985–1995	1996–2006	2007–2020	1985–1995	1996–2006	2007–2020
Men						
Total change	0.216***	0.00791	−0.971***	−0.303***	−0.106***	−0.483***
	(0.021)	(0.015)	(0.013)	(0.022)	(0.011)	(0.007)
Observations	25,507	46,468	78,831	25,507	46,468	78,831
Women						
Total change	0.0842***	0.0790***	−0.988***	−0.163***	−0.160***	−0.553***
	(0.029)	(0.017)	(0.013)	(0.028)	(0.015)	(0.008)
Observations	19,859	38,881	71,544	19,859	38,881	71,544
Urban						
Total change	0.0931***	0.268***	−0.896***	−0.170***	−0.308***	−0.549***
	(0.020)	(0.014)	(0.012)	(0.025)	(0.014)	(0.007)
Observations	23,159	50,299	87,942	23,159	50,299	87,942
Rural						
Total change	0.123***	−0.337***	−1.004***	−0.238***	0.0432***	−0.464***
	(0.026)	(0.020)	(0.011)	(0.021)	(0.011)	(0.010)
Observations	22,207	35,050	62,433	22,207	35,050	62,433
Birth cohort (< = 1974)						
Total change	0.0590***	0.321***	−1.149***	0.0810***	−0.0812***	−0.676***
	(0.019)	(0.020)	(0.013)	(0.020)	(0.020)	(0.007)
Observations	28,998	35,903	74,650	28,998	35,903	74,650
Birth cohort (>1974)						
Total change	0.0798***	0.0853***	−0.610***	0.0498*	−0.0228**	−0.309***
	(0.030)	(0.012)	(0.009)	(0.026)	(0.010)	(0.009)
Observations	16,368	49,446	75,725	16,368	49,446	75,725
Age 15–29						
Total change	−0.111***	−0.173***	−0.670***	−0.349***	−0.0536***	−0.310***
	(0.019)	(0.012)	(0.011)	(0.020)	(0.011)	(0.012)
Observations	18,638	28,177	30,799	18,638	28,177	30,799
Age 30–44						
Total change	0.126***	0.0186	−0.655***	−0.115***	−0.216***	−0.495***
	(0.025)	(0.015)	(0.012)	(0.030)	(0.015)	(0.008)
Observations	19,226	37,954	58,726	19,226	37,954	58,726

(Continued)

Table 7. (*Continued*)

	90-50			50-10		
	1985–1995	1996–2006	2007–2020	1985–1995	1996–2006	2007–2020
Age 45–60						
Total change	−0.0247	0.240***	−1.751***	0.0332	−0.199***	−0.781***
	(0.056)	(0.041)	(0.021)	(0.056)	(0.041)	(0.010)
Observations	7,502	19,218	60,850	7,502	19,218	60,850

Robust standard errors in parentheses
***p < .01,
**p < .05,
*p < .1.
Source: Authors' calculations.

younger cohort in the most recent decade. For the 50–10 gap, both cohorts show a decline from 1996 to 2020, with a larger magnitude for the older cohort.

The decomposition results for different age groups show that for ages 15 to 29, both the 90–50 and 50–10 gaps decrease for all time periods. For ages 30 to 44, the 90–50 gap starts to decrease in the last time period, while the 50–10 gap displays a decreasing trend over all time periods. The oldest group shows a decline in the 50–10 gap for the last two periods and an increase in the 90–50 gap from 1996 to 2006. Generally, the younger age group experiences a monotonic reduction in the wage gap, while it is mixed for older groups.

Conclusion

The structural change in Thai labour employment has resulted in fewer low-skill workers and more mid-skill workers. Meanwhile, wage inequality has risen for high-skill and middle-skill workers and fallen for middle-skill and low-skill workers, indicating a different driving force compared to that in developed countries. This study explores the return on job requirements by brain and brawn and wage polarisation by examining the changes in wage distribution in Thailand in the past thirty years. We followed Rendall (2013) and assigned occupation-industry skill pairs by ordinal ranks of brain and brawn requirements using the DOT. We quantify the contribution of changes in the occupational and industrial skill requirements over time and highlight the increase in the return on the brain and the decrease in the penalty on brawn, which helps explain the wage distribution changes across periods. Using the FFL decomposition approach introduced by Firpo et al (2009), we estimate the changes in the wage distribution based on three time periods. The findings suggest that wage dispersion increases in the top end over the first two time periods but decreases in the third time period, while it continues to decrease in the lower end of the distribution.

Data availability. The data that support the findings of this study are available from the NSO of Thailand.

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Competing interests. The authors declare that they have no competing interests.

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Ethical standards. This article does not contain any studies with human participants or animals performed by any of the authors.

Notes

1 The occupational groups are harmonised based on the International Standard Classification of Occupations 2008 (ISCO-08).
2 The wage is deflated by the Thailand Consumer Price Index, obtained from the Bureau of Trade and Economic Indices, Ministry of Commerce, Thailand.
3 In 2001, National Statistical Office defined the labour force population as any individual aged 15 or older.
4 The industry ordinal sorting from low to high for brain (brawn) requirements is as follows: 1. Agriculture (finance and business service), 2. Transport and telecommunications (retail and hotels), 3. Manufacturing (communal services), 4. Mining (manufacturing), 5. Retail and hotels (transport and telecommunications), 6. Construction (public service), 7. Public services (mining), 8. Communal services (construction), and 9. Finance and business service (agriculture). The occupation ordinal sorting from low to high for brain (brawn) requirements is as follows: 1. Elementary occupations (clerks), 2. Plant and machine operators (legislators, officials and managers), 3. Service workers and sales (professionals), 4. Craft workers (technicians), 5. Skilled agricultural workers (service workers and sales), 6. Clerks (plant and machine operators), 7. Technicians (craft workers), 8. Legislators, officials and managers (elementary occupations), and 9. Professionals (skilled agricultural workers). The detailed factor compositions and definitions for brain and brawn are illustrated in Rendall (2013).
5 The factor composition for the job characteristics and factor scoring coefficients for brawn and brain using DOT are presented in Table 4 in Rendall (2013).
6 Note that from Table 2 (Column (3)), 2007–2020, the coefficient on age square is positive, which contradicts what we expected from typical Mincerian wage regression. This result implied that for workers who continuously stayed in the labor market, their earnings increased at an increasing rate. The post-school investment could help us to explain this result. The Thai Government has heavily and continuously promoted skill development in the workplace. Government, private sector organisations, and the community have offered formal and informal training, increasing workers' earnings. For example, the Skill Development Promotion Act B.E. 2545 (A.D. 2002) has been issued to encourage business units to upgrade workforce skills.
7 As brain/brawn skills are computed using the average standardised factor composition, and it is hard to divide by different levels and cannot address the issue by providing an average wage based on the index, we, therefore, calculated the return on brain/brawn skills and graphed the trend instead (Figure 3).
8 We have also performed a single regression with a gender dummy interacting with brawn and brain variables and obtained findings similar to our original regression in Table 3. We have presented the results in Table A1 in the appendix.
9 The wage penalty for the number of children in 1985–1995 was roughly double for men relative to women, implying that the higher the number of children, the higher the fatherhood penalty. During that period, men were head of household and family breadwinners and more attached to the formal labor market than women. Women were mainly in the informal labor market; they could accommodate childcare and working part time, resulting in fewer wage penalties than men. However, the effect of the parenthood penalty has intensified less from 1996–2006 as the fertility rate in Thailand was very low (around 1.5). The adverse effects of the number of children on men's and women's wages become less compared to other periods.
10 We have also performed a single regression with an urban dummy interacting with brawn and brain variables and obtained findings similar to our original regression in Table 4. We have presented the results in Table A2 in the appendix.

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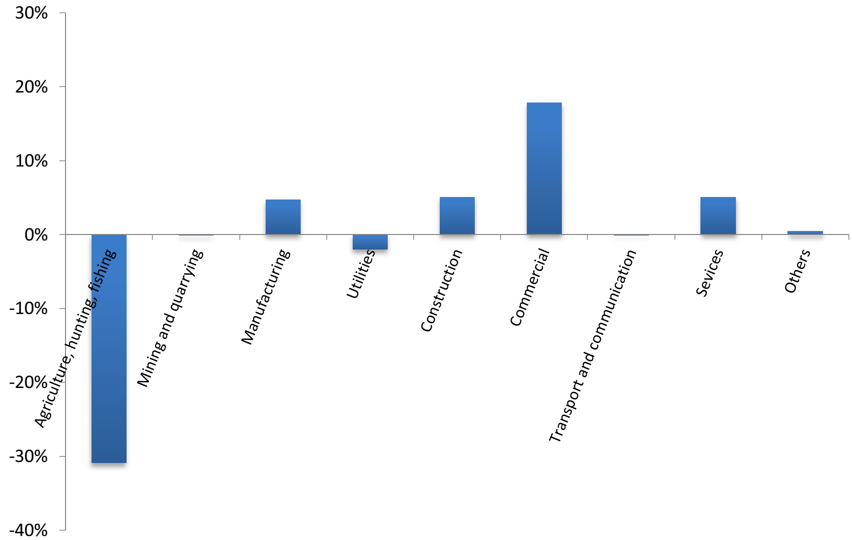
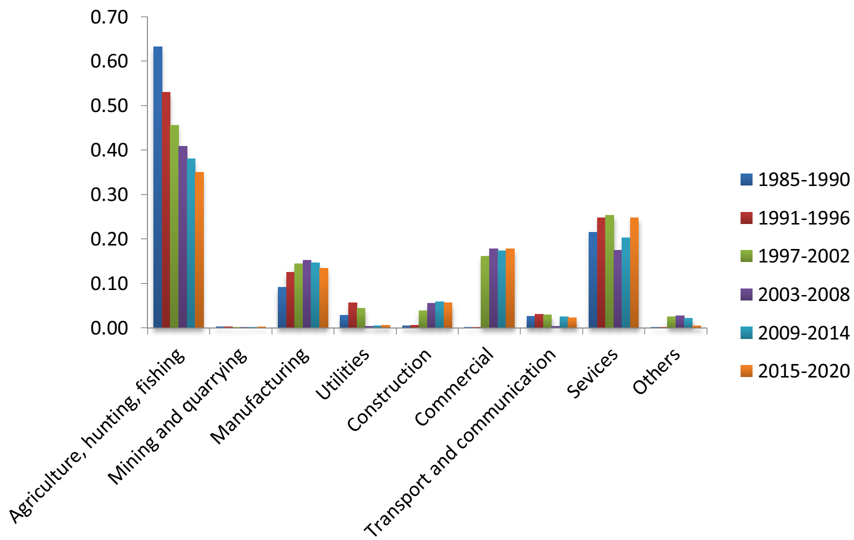
Appendix A



Panel a) Change in shares of employment in each industry (1985 vs 2020)



Panel b) Shares of employment in each industry overtime (1985-2020)

Figure 1A. Share of employment in each industry (1985–2020).
Source: Authors' calculations from Thailand's Labour Force Survey (1985–2020), conducted by the National Statistical Office.

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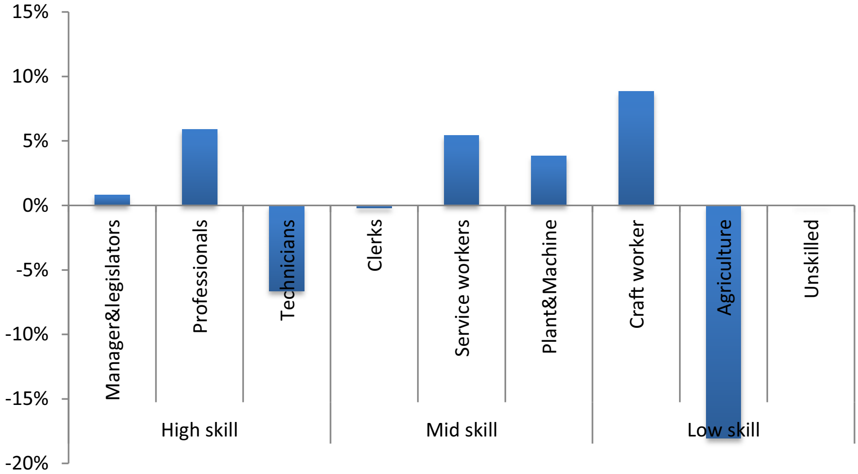
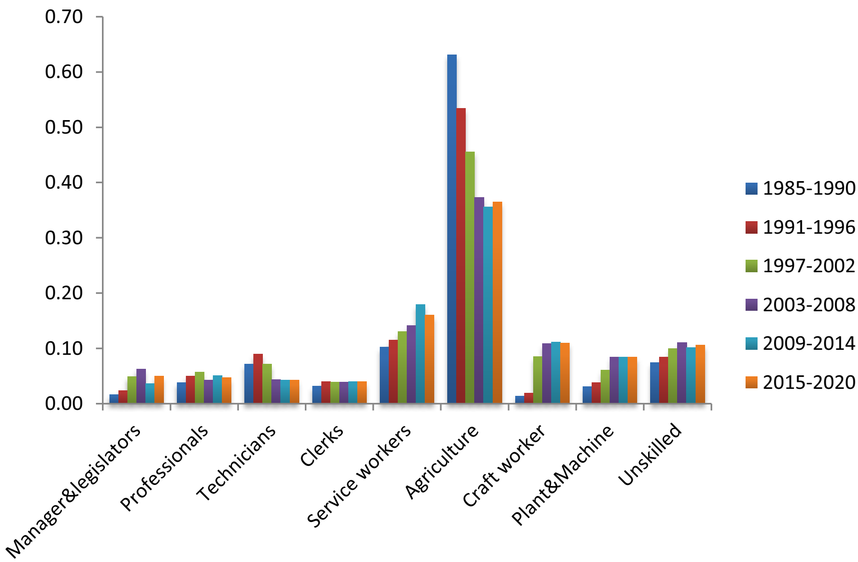


Panel a) Change in shares of employment in each occupation (1985 vs 2020)



Panel b) Shares of employment in each occupation overtime (1985-2020)

Figure 2A. Share of employment in each industry in each occupation (1985–2020).
Source: Authors' calculations from Thailand's Labour Force Survey (1985–2020), conducted by the National Statistical Office.

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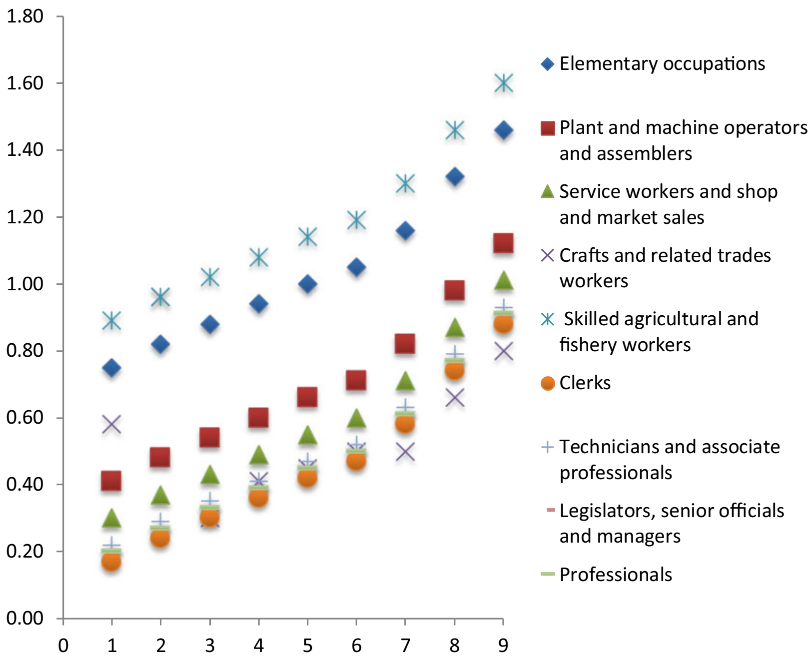

Figure 3A. Skill intensity for brawn by occupation and industry.

Note. For x-axis, 1 = Finance and business services; 2 = Retail, hotels; 3 = Communal services; 4 = Manufacturing; 5 = Transport and telecommunications; 6 = Public services; 7 = Mining; 8 = Construction; 9 = Agriculture, hunting, etc.

Source: Following Rendall (2013), skill intensity for brawn by occupation and industry was calculated by authors from Labour Force Survey.

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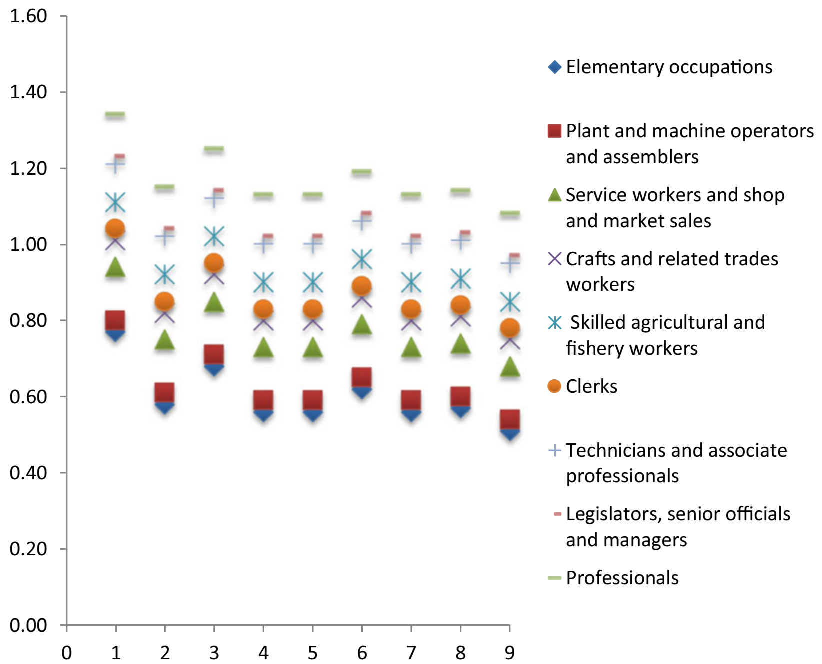

Figure 4A. Skill intensity for the brain by occupation and industry.
Note. For x-axis, 1 = Finance and business services; 2 = Retail, hotels; 3 = Communal services; 4 = Manufacturing; 5 = Transport and telecommunications; 6 = Public services; 7 = Mining; 8 = Construction; 9 = Agriculture, hunting, etc.
Source: Following Rendall (2013), skill intensity for brain by occupation and industry was calculated by authors from Labour Force Survey.

Table A1. The results of wage regression on brawn and brain with interaction terms (Gender dummy: female = 1, male = 0)

	(1) 1985–1995	(2) 1996–2006	(3) 2007–2020
Brawn	−0.284***	−0.195***	−0.128***
	(0.005)	(0.003)	(0.005)
Brain	0.196***	0.616***	0.851***
	(0.008)	(0.005)	(0.010)
Brawn*Gender	−0.203***	−0.146***	−0.138***
	(0.005)	(0.003)	(0.006)
Brain*Gender	−0.0216***	−0.0595***	−0.0182***
	(0.004)	(0.003)	(0.005)
Age	0.0615***	0.0310***	0.000719
	(0.001)	(0.001)	(0.001)
Age square	−0.000451***	−5.84e-05***	0.000160***
	(0.000)	(0.000)	(0.000)
Year of schooling	0.109***	0.0953***	0.0608***
	(0.000)	(0.000)	(0.000)
No. of children	−0.0170***	−0.00315***	−0.0251***
	(0.001)	(0.001)	(0.001)
Marital status	0.147***	0.106***	0.0738***
	(0.003)	(0.002)	(0.003)
Control for regions	Yes	Yes	Yes
Constant	1.184***	1.632***	2.758***
	(0.015)	(0.010)	(0.020)
Observations	194,267	433,196	657,676
R-squared	0.646	0.633	0.565

Robust standard errors in parentheses
***$p < .01$,
**$p < .05$,
*$p < .1$.
Source: Authors' calculations.

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Table A2. The results of wage regression on brawn and brain with interaction terms (Urban dummy: urban = 1, rural = 0)

	(1)	(2)	(3)
	1985–1995	1996–2006	2007–2020
Brawn	−0.390***	−0.233***	−0.0708***
	(0.004)	(0.003)	(0.002)
Brain	0.178***	0.543***	0.810***
	(0.008)	(0.005)	(0.004)
Brawn*Urban	0.0506***	−0.0107***	−0.0624***
	(0.006)	(0.003)	(0.003)
Brain*Urban	0.0256***	0.0625***	0.125***
	(0.005)	(0.003)	(0.002)
Age	0.0611***	0.0288***	0.00194***
	(0.001)	(0.001)	(0.000)
Age square	−0.000442***	−2.97e-05***	0.000209***
	(0.000)	(0.000)	(0.000)
Year of schooling	0.108***	0.0948***	0.0712***
	(0.000)	(0.000)	(0.000)
No. of children	−0.0177***	−0.00202***	−0.0180***
	(0.001)	(0.001)	(0.001)
Marital status	0.169***	0.119***	0.0779***
	(0.003)	(0.002)	(0.001)
Control for regions	Yes	Yes	Yes
Constant	1.140***	1.643***	2.296***
	(0.015)	(0.010)	(0.009)
Observations	194,267	433,196	657,676
R-squared	0.639	0.626	0.559

Robust standard errors in parentheses
***$p < .01$,
**$p < .05$,
*$p < .1$.
Source: Authors' calculations.

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