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Brain over Brawn: Job Polarization, Structural Change, and Skill Prices

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Abstract:

This study investigates the effects of brain and brawn skills on wages and the changes in wage distribution in Thailand using the Labor Force Survey (LFS) from 1985 to 2020. We quantify the contribution of changes in the skill requirement and highlight the increase in the return on brain and the decrease in the penalty on brawn, which helps explain the wage distribution changes across periods. We further explore the polarization in the labor market and analyze 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:

polarization, structural change, RIF-regressions, decomposition, wage inequality, job tasks

JEL Classification: J20, J23, J24, J31

1. Introduction

A large body of research examined the increase in wage inequality in both 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, 1992). Recently, the role of occupations in wage inequality changes has begun to draw a great deal of attention in developed countries. Autor et al. (2006, 2008) document the trend of wage polarization in the US caused by a decline in the demand for middle-skilled workers and provide an explanation based on skilled-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 labor in developing countries (Blinder, 2009; Jensen and Kletzer, 2010; Firpo et al., 2011). Automation has increased the demand for both skilled and low-skilled non-routine jobs (Autor et al., 2003; Goos and Manning, 2007). Buera et al. (2018) use skill-biased structural change to describe the systematic reallocation of sectoral value-added shares to high-skill-intensive industries that are associated with the increase in demand for high-skill workers, contributing to the increased skill premium in advanced countries.

Given their different occupational structures and the impact of offshoring, recent technological progress, which has been driving labor market polarization in developed countries, should result in different dynamics in developing countries. However, unlike in developed countries, polarization in developing countries has not attracted much attention. Reijinder and Vries (2017) find that job polarization 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 for investigating the return on skills and polarization. Thailand has experienced an economic expansion that transformed it from a low-income country to 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-based economy (Vanitcharearnthum, 2019).

In this study, we first explore the effects of brain and brawn skills on wages. 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 allows 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 polarization in the labor market and analyze 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 in DiNardo et al. (1996) with the classic Oaxaca-Blinder (OB) decomposition method by Oaxaca (1973) and Blinder (1973) and employs a recentered influence function (RIF) regression to provide the decomposition of any distributional parameter, such as quantiles or Gini coefficients.

We provide new evidence regarding wage polarization 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 polarization 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 increase in wages for high-skill workers compared to middle-skill workers, as well as the decrease in the gap between lower- and middle-skill workers.

The rest of the paper is organized 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 analyzes the results, and Section 7 concludes.

2. Literature review

An increase in wage inequality has been observed in many developed countries (e.g., Atkinson et al., 2011: Lemieux, 2006a; Autor et al., 2008 for the US; Dustmann et al., 2009; Card et al., 2013 for Germany; Machin, 2003 for the UK; Koeniger et al., 2007 for 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., Katz and Autor, 1999; Autor et al., 2008; Acemoglu and Autor, 2011; Maarek and Moiteaux, 2021), which explains the expansion of wage dispersion both between and within education groups (Katz and Murphy, 1992; Goldin and Katz, 2009). 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 wage inequality increases (DiNardo et al., 1996; Lemieux, 2006a; Card et al., 2013; Bienwen et al., 2017; Antonczyk et al., 2018).

More recently, as studies have suggested that a general increase in wage inequality is not sufficient to describe the recent labor market trends, Autor et al. (2003) have introduced the task approach and propose a nuanced version of SBTC, in which technology can replace human labor in routine tasks but not in non-routine tasks, leading to the polarization in the labor market. Goos and Manning (2007) also show evidence of polarizing employment in the UK, which supports Autor et al.'s (2003) hypothesis. Many later studies have shown the pervasiveness of job polarization in other developed countries (Dustmann et al., 2009; Katz and Margo, 2013; Goos et al., 2009; Park et al. 2022).

Job polarization in the US has been accompanied by wage polarization, 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 polarization and wage inequality occur concurrently, the link between the two is still unknown. Studies have suggested that wage polarization 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.

Another aspect of the change in the wage structure through occupations in developed countries lies in the expansion of offshoring opportunities, allowing foreign labor 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 comparatively small or negligible role, while Firpo et al. (2009) find that offshorability is significant in explaining wage polarization. Autor et al. (2015) suggest that China's rapid rise in manufacturing has a far-reaching impact on US workers by reducing employment and depressing labor 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 polarization has become one of the most discussed topics in labor economics in developed countries, it is rarely considered in developing countries, given the difference in occupational distributions, the impact of off-shored jobs from developed countries, and the impact of technological progress. Maloney and Molina (2016) find no evidence of polarization in developing countries on average, but a few countries, like Indonesia, Mexico, and Brazil, show some evidence of incipient polarization. Danieli (2013) finds evidence of wage polarization in Israel, and Helmy (2015) shows that job polarization is growing with the expansion of wage disparity in Egypt.

In developing countries, a large share of the labor force is employed in agriculture, while middle-skill workers occupy only a small proportion. Therefore, Maloney and Molina (2016) indicate the potential polarization 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 in developing countries, which may result in "de-polarization" for countries like China. Reijinder and Vries (2017) suggest that while offshoring has contributed to polarization in developed countries, the opposite effect, "anti-polarization," is seen in major offshore destinations such as China and Eastern Europe. Furthermore, under globalization, 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., Juhn et al., 1993; Card, 2001; Autor et al., 2003). 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 technology 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., Meesook, 1979; Krongkaew, 1985; Israngkura, 2003; Warr and Isra Sarntisart, 2005; Motonishi, 2006; Kurita and Kurosaki, 2011; Paweenawat and McNown, 2014; Kilenthong, 2016). As an exception, Lathapipat (2009) suggests that wage polarization 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 very limited effect 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 low-skill workers. Paweenawat (Forthcoming) 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.

3. Study background

In this section, we provide an overview of the changes in occupational composition, wage structure, and education in Thailand's labor market between 1985 and 2020, and explore the changes in the employment structure that are relevant to the job polarization found in developed countries. We draw attention to the development of wage inequality and provide information on how the Thai labor 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 1A 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, which is similar to the changes in industrial employment (Figure 2A in Appendix). Middle-skill employment has increased, but high-skill employment has shown relatively little change over time.

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 relatively stable pattern for high-skill employment (1%). Therefore, we do not observe job polarization in Thailand since agriculture has accounted for a large share of the labor force from the beginning, with a low share of middle-skill employment. Instead of job polarization, 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., Knodel, 1997; Hawley, 2004; Motonishi, 2006; Paweenawat and McNown, 2014). Less widely recognized is the change in inequality between different educational and occupational skill groups. In the US, wage polarization 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 both educational groups 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 continues to increase, while real wage growth for middle-skill occupations stagnates until 2011.

Generally, labor employment has transferred from agriculture to manufacturing and service industries, resulting in fewer low-skill workers and more middle-skill workers. Unlike the US with its U-shaped employment shares and wage growth by percentile (Autor et al., 2010), in Thailand, low-skill workers experienced the highest wage growth during the last three decades and the largest drop in employment. The wage gap between high-skill and middle-skill workers has expanded while the gap between middle-skill and low-skill workers has contracted.

A possible explanation is that the increase in education has not provided an adequate number of high-skill workers, indicating a quality mismatch in the Thai labor market (Satimanon, 2017), while improvement in technology has increased the demand for more high-skill workers (Tinbergin, 1974, 1975; Autor et al., 2010) 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 among university graduates in Thailand 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-skill workers, such as more analytical work, and by low-skill workers, like non-routine manual work, cannot be supplemented by machines, which increases the demand for them (Autor et al., 2010). However, for low-skill workers, the situation in Thailand is quite different. Unlike developed countries, low-skill employment has historically dominated the labor market, as agriculture accounts for the largest share of employment. The economic development during the last three decades has moved laborers from agriculture to other industries. Up to one million people per year transferred from agriculture to urban occupations, and real per capita income doubled (Phongpaichit and Baker, 2008). Thailand has changed from a low-income country to an upper-income country (World Bank, 2019), as wages at the low end of the distribution have increased substantially over time.

Ideally, our goal is to estimate changes in wage distribution using a dataset that contains detailed task content of occupations and skill requirements for jobs with large sample sizes. However, in developing countries, it is difficult to find job task requirements like those available from the Dictionaries of Occupational Titles (DOT) or O*NET from the US Department of Labor. 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 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 labor market over time.

4. Data

The data used in this study are from Thailand's Labor Force Survey (LFS) from 1985 to 2020, a survey conducted by the National Statistical Office. We only 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 include 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[1]. As the LFS does not directly provide hourly wages, they are calculated by dividing weekly wages by the sum of workers' working hours. The sample is restricted to workers between the ages of 15 and 60[2]. Individuals are assigned to three mutually exclusive educational groups based on their education levels. The primary level includes those with no, some, or completed primary level education; the secondary level includes those with some or completed

[1] The wage is deflated by the Thailand Consumer Price Index (CPI), obtained from the Bureau of Trade and Economic Indices, Ministry of Commerce, Thailand.
[2] In 2001, NSO defined the labor force population as any individual age 15 or older.

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 Ph.D. degree). The key set of covariates includes years of schooling, age, age squared, occupational dummies, marital status, number of children, and five regional dummies.

The occupational groups are harmonized based on the International Standard Classification of Occupations 2008 (ISCO-08). Similar to Autor et al. (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."

The data were divided into three time periods for the analysis[3]. The first period is 1985 to 1995, the fast growth period preceding the financial crisis. The second time period, 1996 to 2006, including the 1997 crisis, has stagnant wage growth, especially for the high end of the wage distribution. The final period is 2007 to 2020, covering several economic events[4], which shows fast growth for the low end and a declining trend moving to the higher end of the distribution. Table 1 reports the descriptive statistics in three periods, where we obtain 194,267, 433,196, and 675,676 observations, respectively. Wage and education have increased throughout time, while the number of children has decreased.

5. Methodology

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) normalize the skills to percentiles for other countries, assuming that skill requirement ranks for occupations and

[3] In 1996, the National IT Committee (NITC) has announced the first National IT policy, IT2000. The Tenth National Economic and Social Development Plan (2007-2011) is the primary plan to improve the social and economic conditions in Thailand, which refers to promote ICT in various aspects (Ministry of Information and Communication Technology 2009). The ICT development strategy includes producing graduates who have the skills to meet the requirement of the industries and further improving the knowledge, skills and potential for ICT professionals working in the industries.
[4] Include global financial crisis in 2008, Thailand floods in 2011, the Euro zone crisis in 2012, COVID-19 pandemic in 2020, which show a relatively smaller effect on the wage growth, comparing with financial crisis in 1997.

industries in the US match the requirement ranks in other countries on an ordinal scale[5]. For example, technicians require more brain work than agricultural workers in all countries.

By controlling the skill levels for both occupations and industries, we provide additional insights into the structural changes in the labor 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), brain is computed using the average standardized general educational development and specific vocational training, and brawn is computed using the average between physical strength requirements and environmental conditions.[6] The factor composition for brain includes reasoning development and mathematical development, language development, specific vocational preparation, general intelligence, verbal aptitude, clerical aptitude, and talking and hearing. Brawn includes climbing and balancing, stooping/kneeling/crouching/crawling, strength requirements, indoor or outdoor work, and exposure to the environment.

Figure 3A and Figure 4A show the combinations of skill intensity related to brawn and brain, respectively, by occupation and industry. For the same occupation, the requirements for brawn and brain are different in each industry. For example, elementary occupations in the finance and business service industry require less brawn compared to elementary occupations in the agriculture and hunting industries. Professional workers in the finance and business service industry require more brain than professional workers in the agriculture and hunting industry. For each industry, there is also wide dispersion among occupations for brawn and brain. For example, elementary

[5] 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) 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) 9. Professionals (Skilled agricultural workers). The detailed factor compositions and definitions for brain and brawn are illustrated in Rendall (2010, 2013).

[6] The factor composition for the job characteristics and factor scoring coefficients for brawn and brain using DOT are presented Table 4 in Rendall (2013).

and agricultural occupations have a higher need for brawn than other occupations, while professionals, technicians, and managers have a higher need for brain.

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

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

where w_i is the hourly wage of individual 1, 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. S_i indicates the skill requirements (brawn or brain). β represents the skill effect on wages.

Next, we apply the Firpo, Fortin, and Lemieux (FFL) decomposition approach introduced by Firpo et al. (2009) to analyze the wage rate changes. As noted by Firpo et al. (2018), the standard Oaxaca and Blinder (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 (Oaxaca, 1973; Blinder, 1973) and the DFL decomposition method (DiNardo et al., 1996), using the recentered influence function (RIF) of Y as the dependent variable. We focus on the differences in wage distributions between two groups using propensity scores. As suggested by Firpo et al. (2009, 2011), 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, similar to DiNardo et al. (1996), the distributional statistic of interest is decomposed into wage structure and composition components using 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}):

$$\Delta_O^{\nu} = \nu\left(F_{Y_1|T=1}\right) - \nu\left(F_{Y_0|T=1}\right) + \nu\left(F_{Y_0|T=1}\right) - \nu\left(F_{Y_0|T=0}\right) \qquad (2)$$
$$\Delta_O^{\nu} = \qquad \Delta_S^{\nu} \qquad + \qquad \Delta_X^{\nu} \qquad (3)$$

where $\nu\left(F_{Y_1|T=1}\right)$ 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; ν), we can compute the influence function for other distributional statistics (Firpo et al., 2009); our interest is in the wage quantiles. For the τth quantile, the influence function is:

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

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

The RIF of the τth quantile:

$$RIF(y; q_\tau) = q_\tau + IF(y; q_\tau) \qquad (5)$$

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., 2007, 2011).

6. Results

6.1 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 role of structural labor demand, which has a significant effect on the wage distribution.

Table 2 shows the results for skills based on equation (1) for three time periods. The return on brain is positive, indicating higher brain requirements lead to higher wages, while the coefficients for brawn are negative, indicating higher brawn requirements lead to lower wages. The return on 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. Figure 3 further provides the coefficients of the wage regression for brain and brawn by year. While both the coefficients present an upward trend, 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. The return on brain for females is larger than that for males, while the penalty for brawn for females is smaller than that for males, indicating the structural shift changes from brawn skills to brain skills benefits women more in terms of occupational matching and returns. Table 4 presents the results by residence area. The return on brain in urban areas is higher than that in rural areas, indicating a higher demand for skilled labor in urban areas, which correlates with the labor 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 90th, 50th, and 10th 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 brain has a larger impact on the 90th quantile than on the lower wage quantiles. Education has a larger positive impact on the 90th and 50th quantiles than on 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 brain has a larger effect on the 90th quantile. The direction of the effect also changes in different quantiles.

6.2 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 brain increased in the first two time periods, considering the top end related to higher brain skill. In contrast, it decreases in 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 polarization.

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, polarizing wages. Ikemoto and Uehara (2000) suggest that during the latter half of the 1980s and early 1990s, as the leading industry was transformed from export-oriented labor-intensive manufacturing to the financial sector, the wages of high-skill workers increased rapidly because supply lagged far behind demand. However, the wages of production workers could not increase as much as those of skilled workers because of the abundant supply. In the early 1990s, the wages of agricultural labor began to increase as urban industries absorbed the labor.

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 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 (2019) found wage polarization in Thailand from 1987 to 2006, suggesting the SBTC hypothesis is plausible for Thailand. In addition, the large-scale labor 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 ADBI (2019), due to successful policies that allowed financial services to reach the lower end of the income distribution with increased geographical reach (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.

6.3 Disaggregation results

While the basic results reflect the changes in general behavior, the findings may be affected by changes in the composition of the labor market that is 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 improvements in women's education (Nakavachara, 2010; Paweenawat and Liao, 2022).

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 time period (1996 to 2006) are opposite those 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 the reduction in government spending and the lost opportunity of working in urban areas. The rural sector absorbed those who lost jobs in urban areas after the crisis (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 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 during 1996 to 2006. Generally, the younger age group experiences a monotonic reduction in the wage gap, while it is mixed for older groups.

7. Conclusion

The structural change in Thai labor 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 polarization by examining the changes in wage distribution in Thailand over the last three decades. We followed Rendall (2010, 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 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.

Previous educational policies, for example, compulsory education reform in 1978 and 1999, have successfully helped lower wage inequality. Based on our results, governments need more attention to the quality of education, as the increase in education has not provided the labor market with an adequate number of high-skill workers. Strengthening workers' skills and promoting innovation has been one of the most important parts of a country's development strategy. Specifically, policymakers should focus more on 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 labor market (Pitt et al., 2010; Rendall, 2013). Vocational Education and Training (VET) that provides workers with skills and technical knowledge leading to higher payments and better career development is also recommended. The disaggregation results show that the structural transformation changes benefit women more through occupational matching and returns. Governments should further attract firms that provide a better environment in terms of equal opportunities for both men and women.

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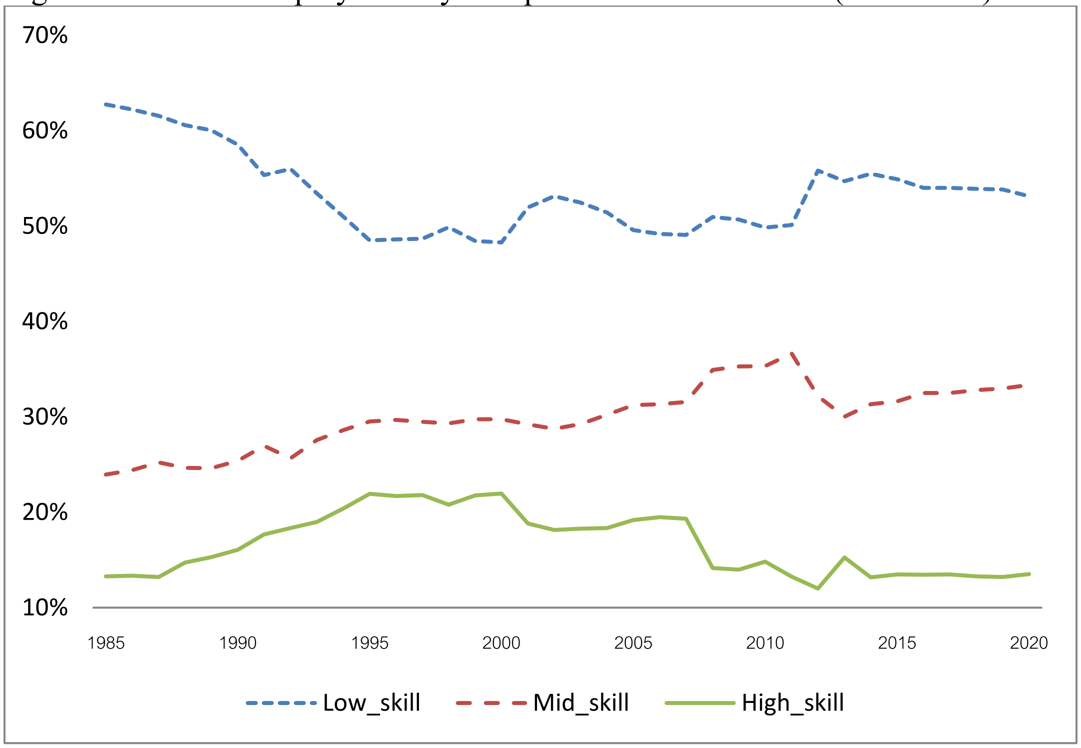
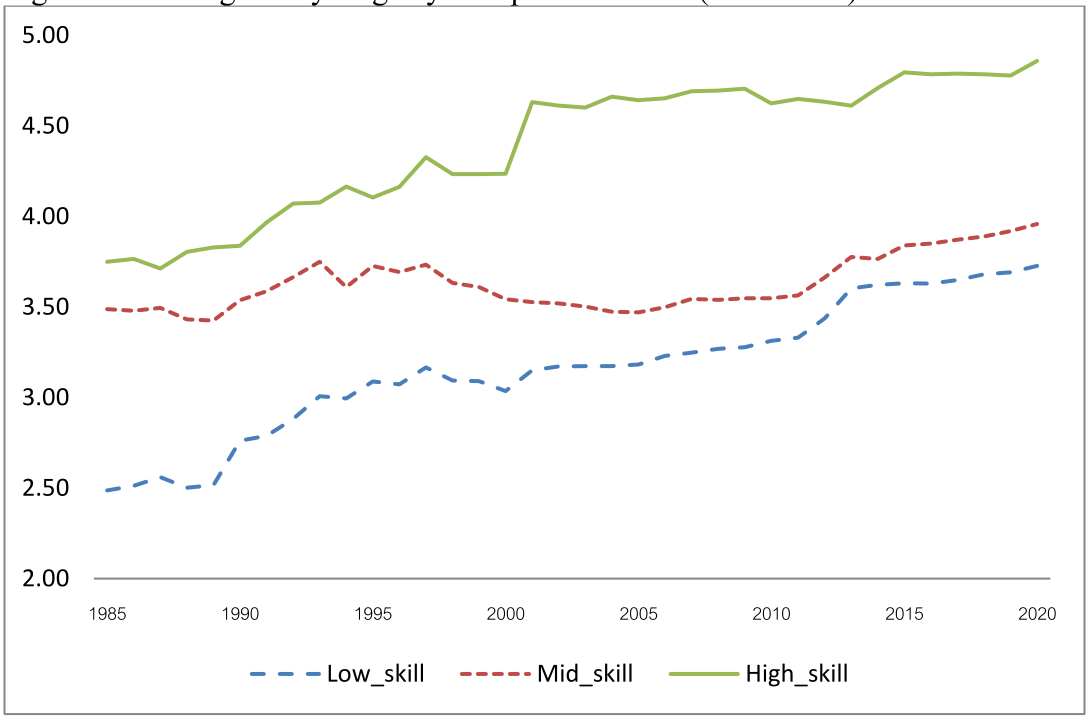
Figure 1. Shares of employment by occupational skills overtime (1985-2020)



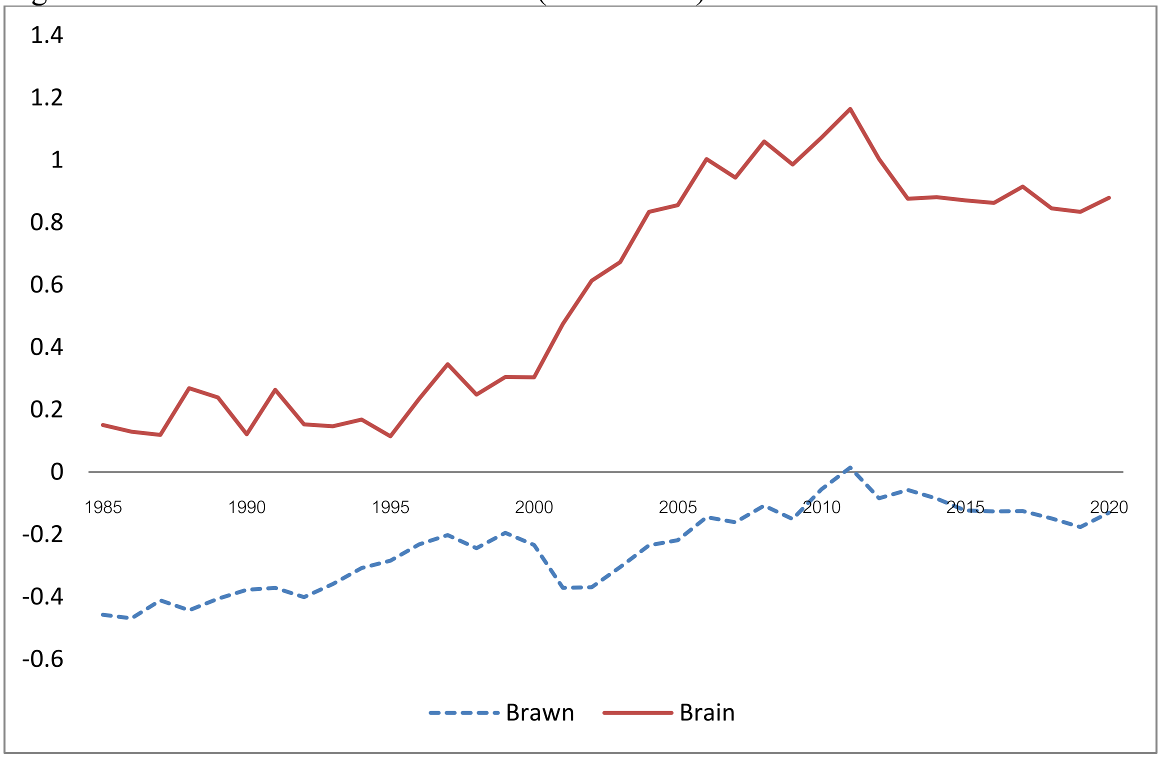
Source: Authors' calculations.

Figure 2. Real log hourly wage by occupational skills (1985-2020)



Source: Authors' calculations.

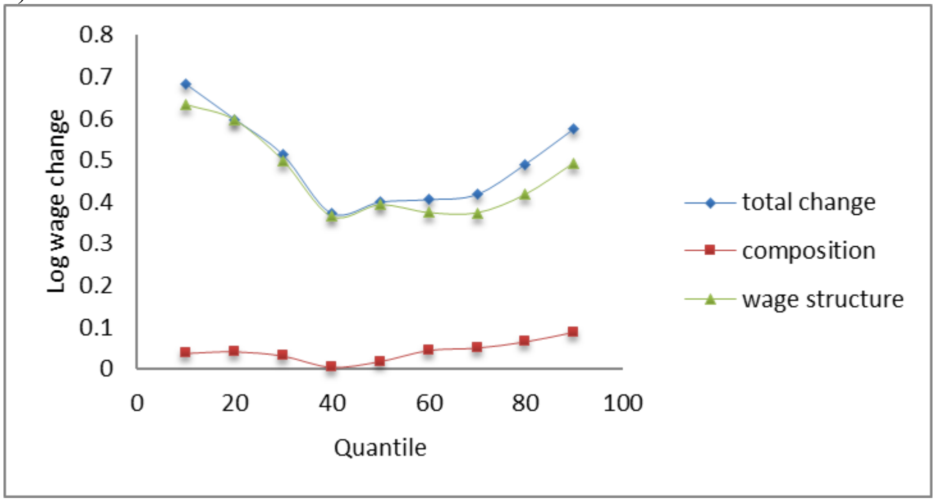
Figure 3. The return on Brawn and Brain (coefficients):



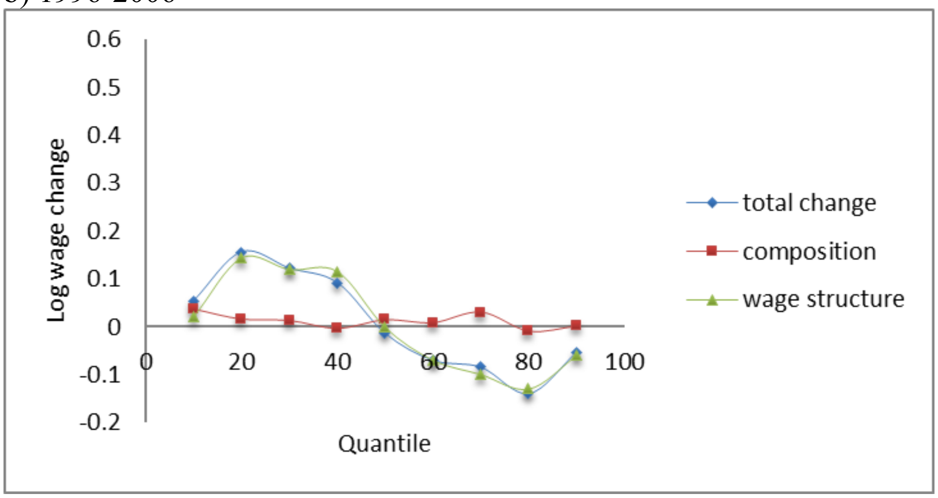
Note: All coefficients are significant at 1%, except 2011 is significant at 10%.
Source: Authors' calculations.

Figure 4. The decomposition of total change into composition and wage structure effect

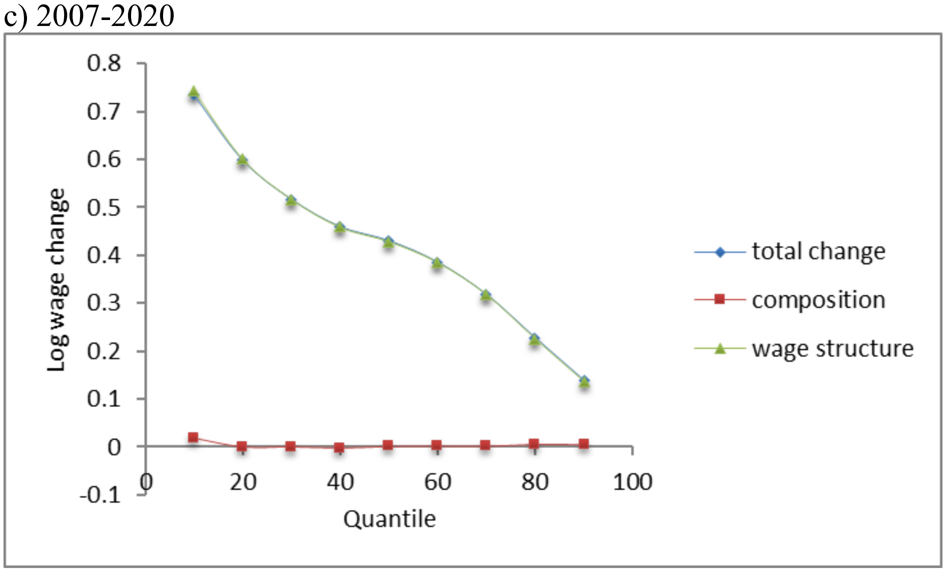
a) 1985-1995



b) 1996-2006



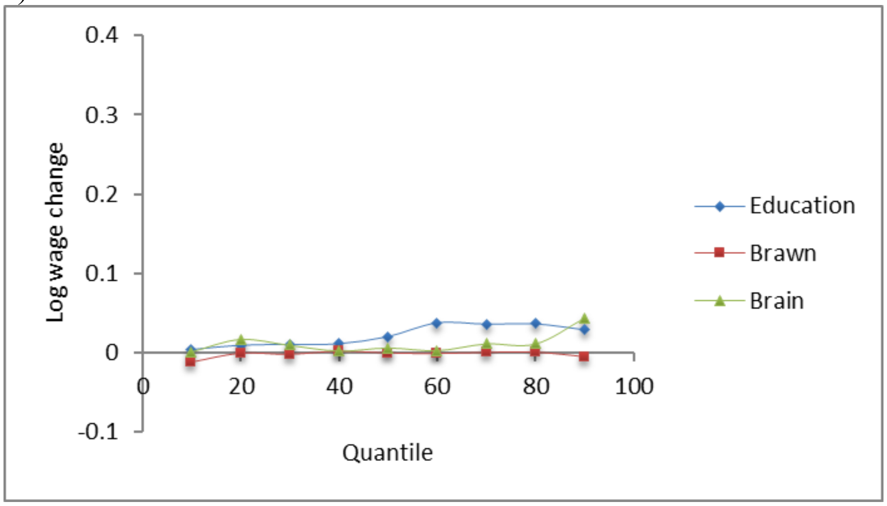
c) 2007-2020



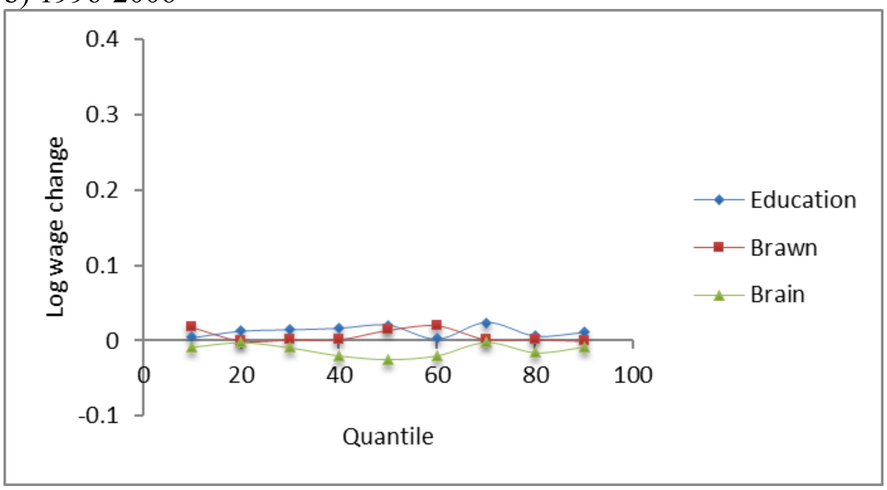
Source: Authors' calculations.

Figure 5. Detailed decomposition for composition effect

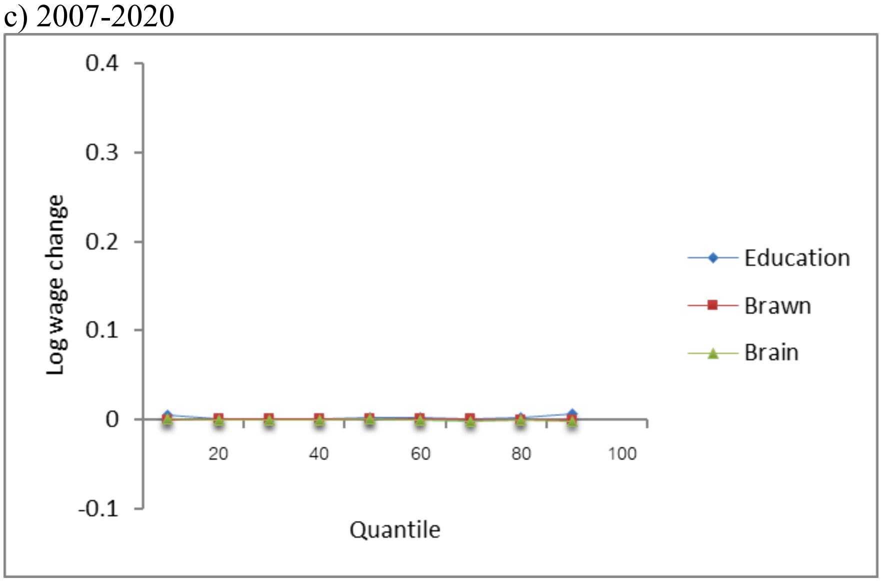
a) 1985-1995



b) 1996-2006



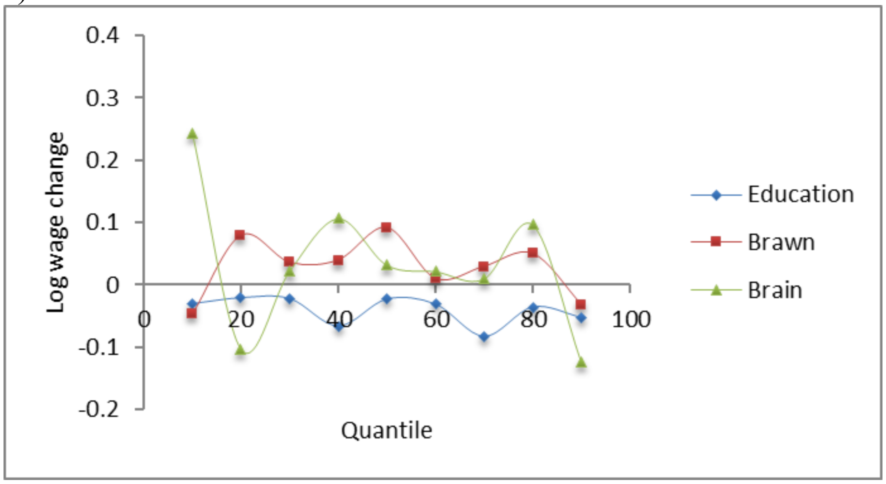
c) 2007-2020



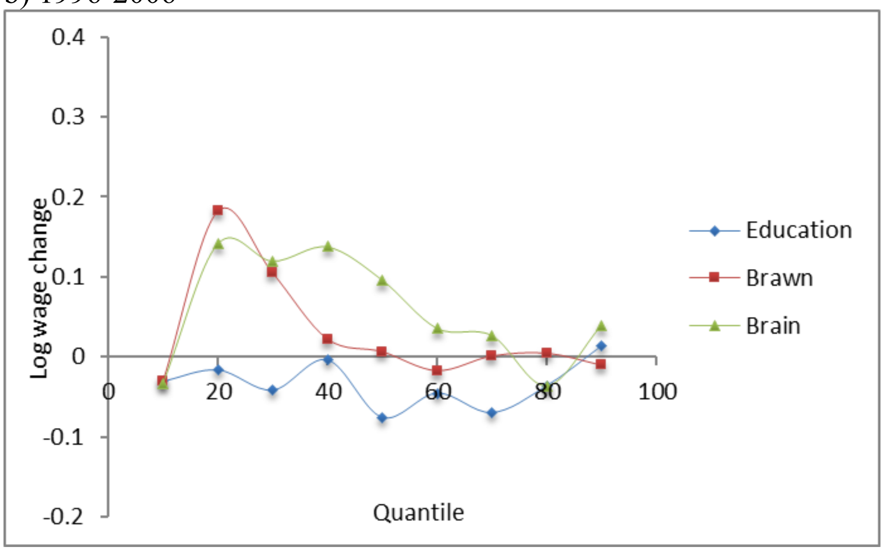
Source: Authors' calculations.

Figure 6. Detailed decomposition for wage structure effect

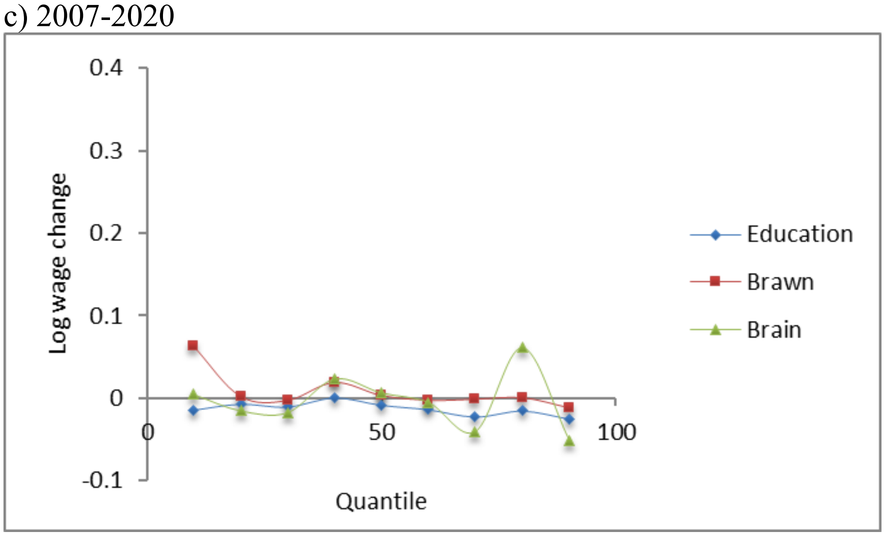
a) 1985-1995



b) 1996-2006



c) 2007-2020



Source: Authors' calculations.

Table 1. Summary Statistics for LFS from 1985-2020

Descriptive Statistics	1985-1995	1996-2006	2007-2020
Log hourly wage	3.437	3.690	3.933
	(0.940)	(0.870)	(0.769)
Gender(1=male;2=female)	1.439	1.458	1.463
	(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)
Observation	194,267	433,196	657,676

Source: Authors' calculations.

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<0.01, ** p<0.05, * p<0.1
Source: Authors' calculations.

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<0.01, ** p<0.05, * p<0.1
Source: Authors' calculations.

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<0.01, ** p<0.05, * p<0.1
Source: Authors' calculations.

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<0.01, ** p<0.05, * p<0.1
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<0.01, ** p<0.05, * p<0.1
Source: Authors' calculations.

Table 7. Disaggregation results

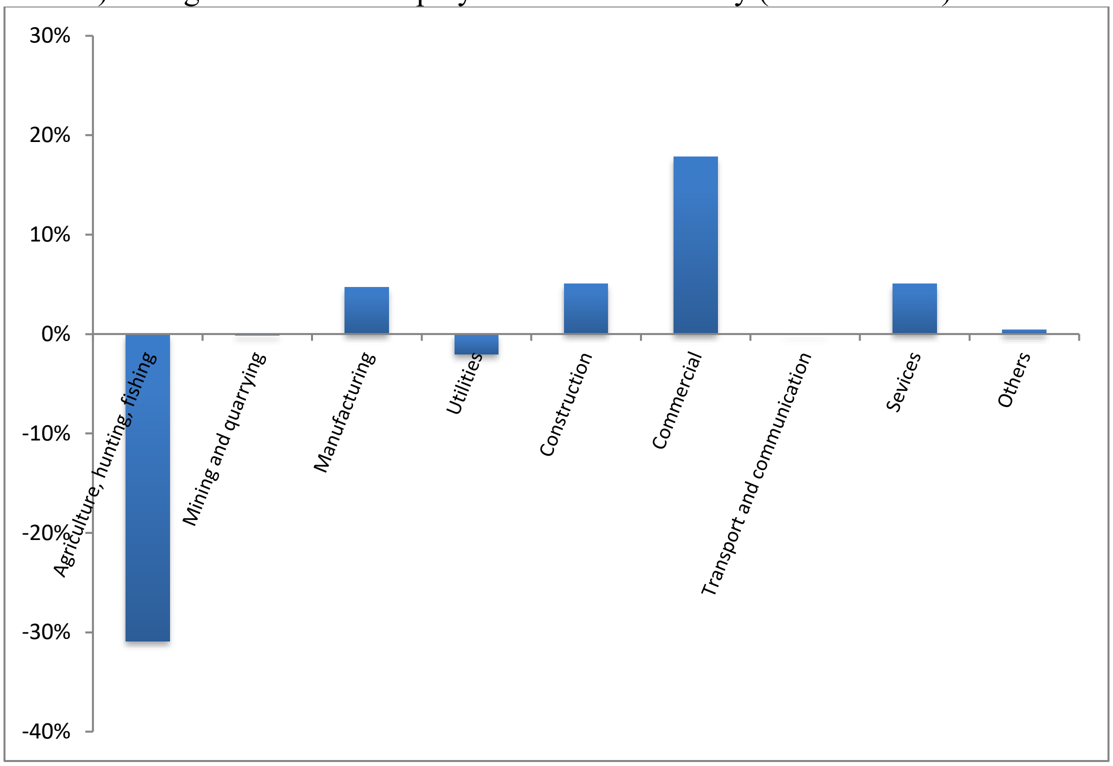
	90-50			50-10		
	1985-1995	1996-2006	2007-2020	1985-1995	1996-2006	2007-2020
Men						
Total change	0.216***	0.00791	-0.971***	-0.303***	-0.106***	-0.483***
	(0.021)	(0.015)	(0.013)	(0.022)	(0.011)	(0.007)
Observations	25,507	46,468	78,831	25,507	46,468	78,831
Women						
Total change	0.0842***	0.0790***	-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
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<0.01, ** p<0.05, * p<0.1
Source: Authors' calculations.

Appendix

Figures1A: Share of employment in each industry (1985-2020)

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



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

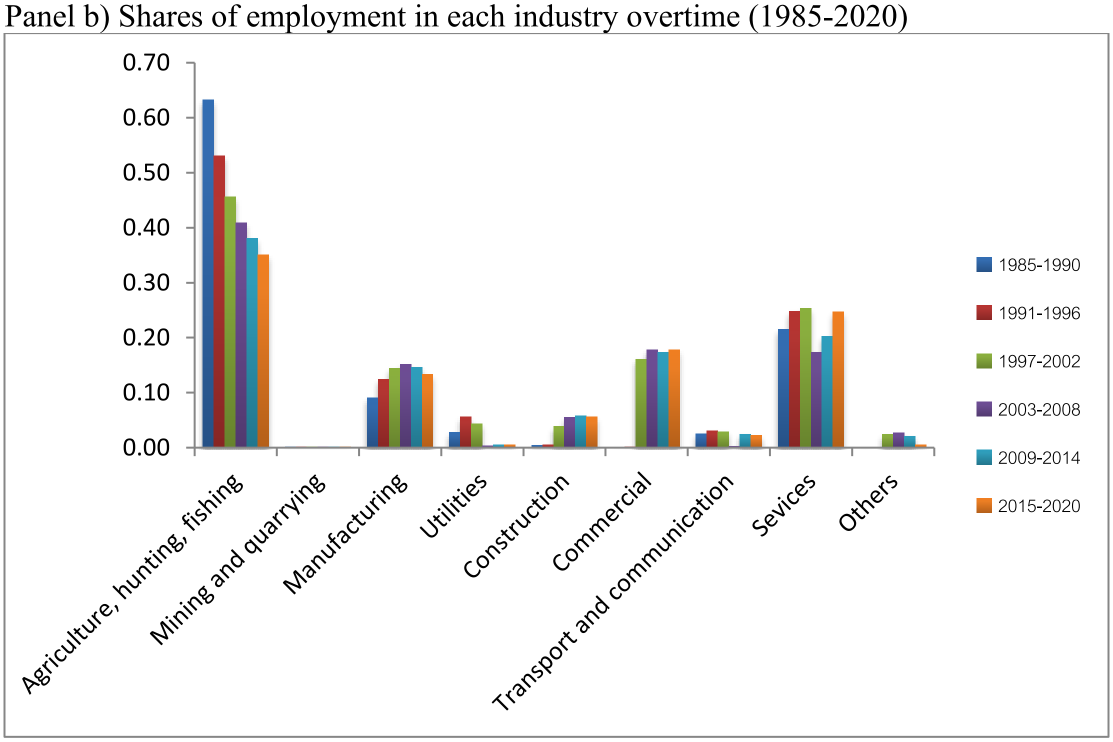
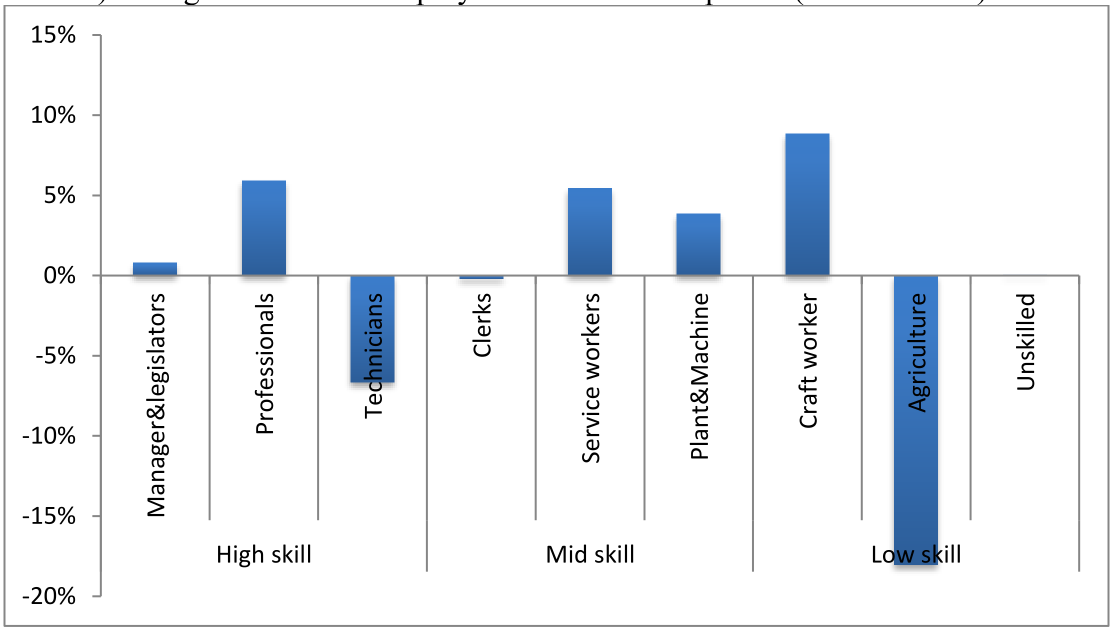


Figure 2A. Share of employment in each industry in each occupation (1985-2020)

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



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

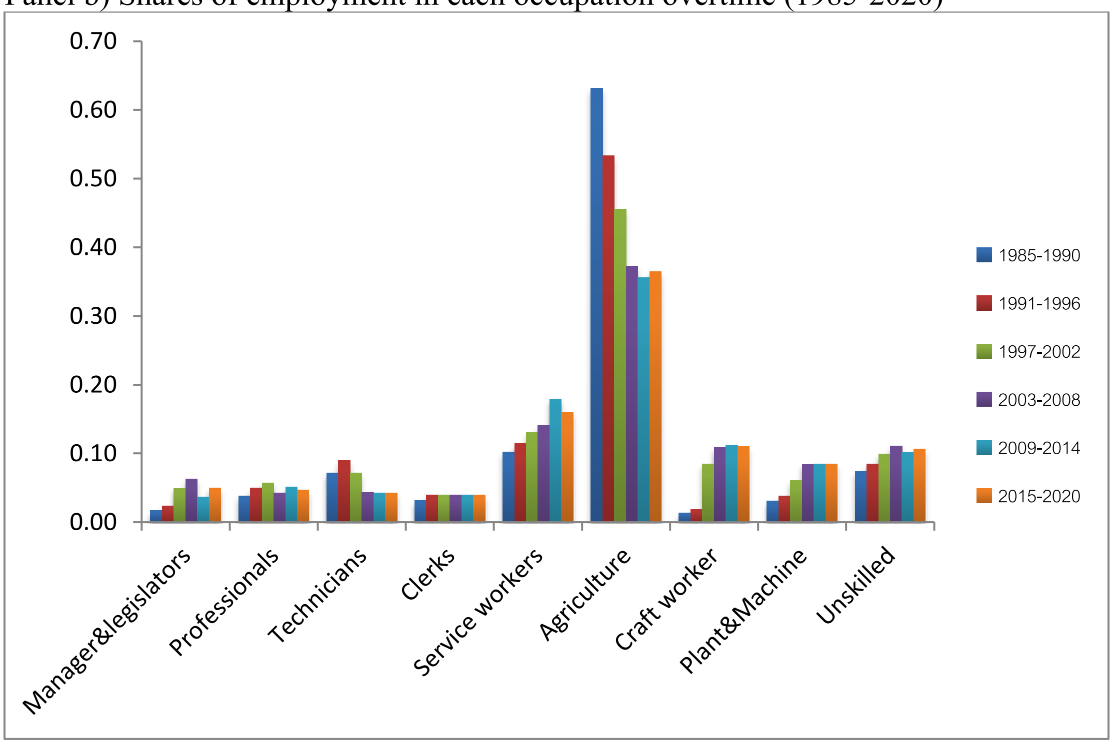
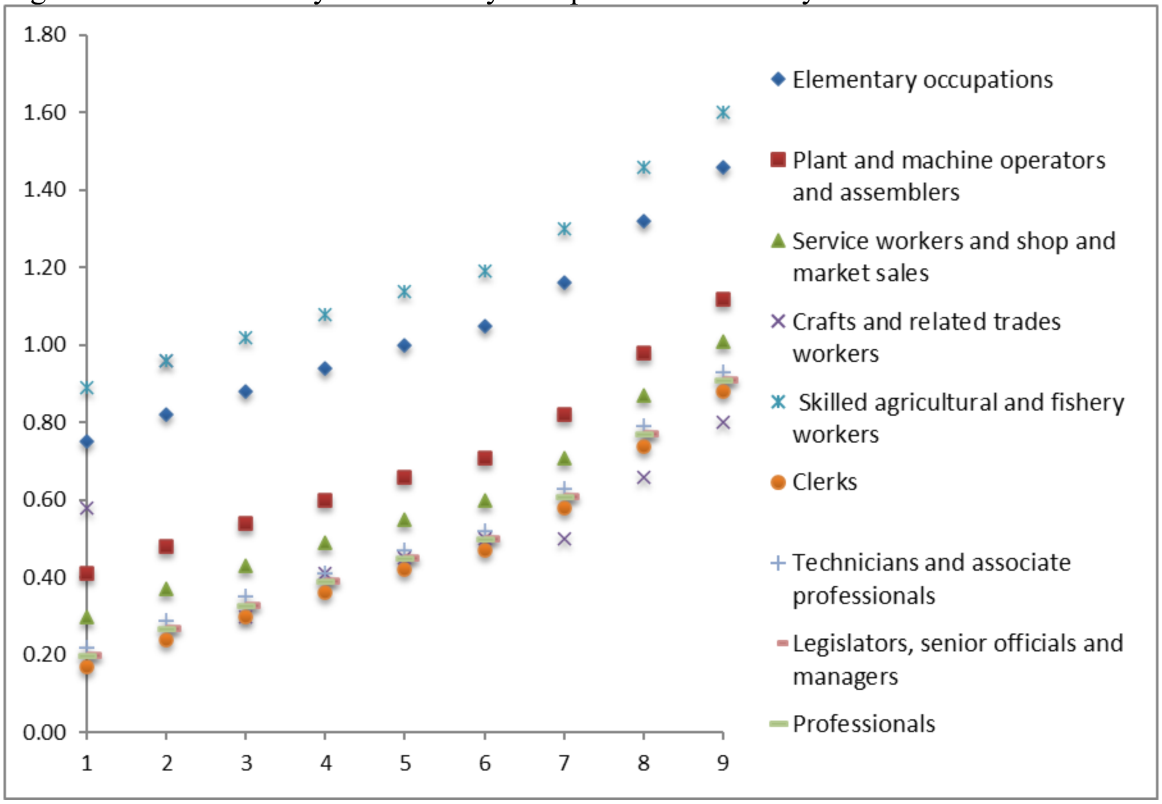
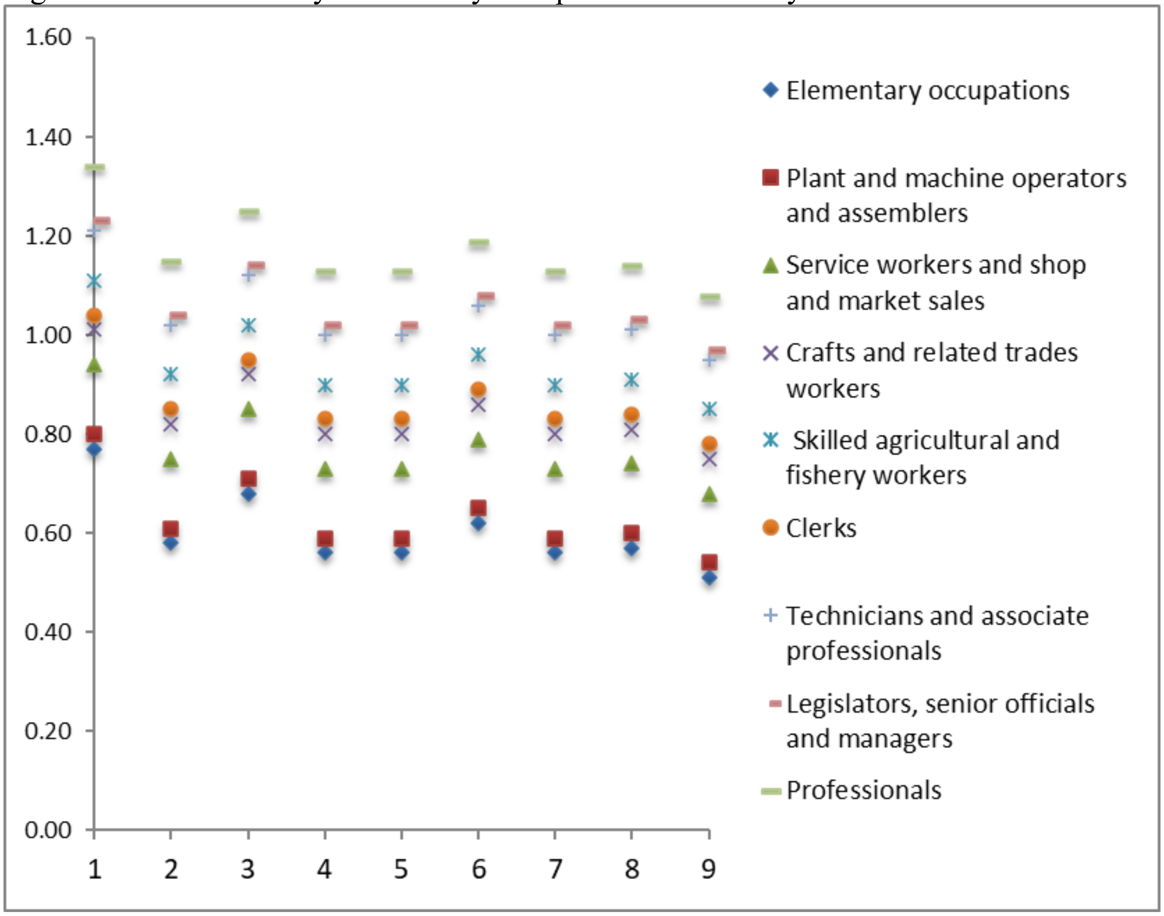


Figure 3A. Skill intensity for brawn by occupation and industry



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.

Figure 4A. Skill intensity for 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. (Rendall 2013)