Educational Attainment and Wage Inequality in Thailand: A Quantile Regression Analysis from 2009 to 2018

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Abstract:
This paper explores the relationship between the educational levels and income inequality of people living in the central region of Thailand from 2009 to 2018. We estimate Mincerian wage equations using ordinary least squares and quantile regression. We find that wage distribution in Thailand, as a result of educational levels, has improved during the period of study. Grouping the population by educational level, it was found that within-group inequality is the largest among university graduates, and the largest decrease in the spread is also found among those with university degrees or higher. Similarly, primary school graduates also record the smallest within-group inequality and the smallest decrease in the spread. The inequality between university graduates and other educational levels has also shrunk. The improvement in income distribution is mainly caused by the decrease in the wage gap around the middle (q25-q75) of the income quantiles while leaving wage differentials at both ends relatively unchanged.

Keywords: *education, income inequality, wage inequality, Mincerian wage equation, quantile regression, Thailand*

1. Introduction

Income inequality is one of the main concerns faced by developed and developing countries. However, this issue tends to be more severe in developing countries like Thailand, which has one of the highest income inequality rates in the world, with the top 10% of the total population sharing 48.8% of the net personal income (World Bank 2023). This figure rises to 74.2% with the inclusion of net personal wealth. In addition, the data from the Credit Suisse wealth report (2022) shows that in 2021, 66.3%[1] of the national wealth is owned by the 10th percentile, 56.4% is owned by the 5th

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1 The corresponding data is 82.9% for Russia, 80.8% for South Africa, and 75.9% for the United States.

percentile, and 39.4%[2] belongs to the 1st percentile of the total Thai population. According to the World Bank, Thailand's inequality has increased over the past few years, and the country's poverty rate grew from approximately 7% in 2015 to almost 9% in 2018. Moreover, Thailand had the highest income Gini coefficient of 43.3% in 2019[3], which is also the highest in the East Asia and Pacific Region. Furthermore, Thailand also ranked 13th among 63 countries with the highest income inequality in the world in 2021 (World Bank 2023). People who reside in rural areas continue to suffer from lower rates of income, low education opportunities, having a large number of dependents, and difficult living conditions. Thus, the income inequality problem in Thailand is a serious matter that needs to be addressed.

There are many factors causing the increasing income inequality, some of which are obvious and some ambiguous. The most discussed factors are, for example, gender, geography, ethnicity, education, skill, globalization, and technology. Despite being a source of inequality, education is encouraged in every country around the world as one way to break the cycle of poverty. From this aspect, education can be seen to lower the inequality gap by getting people out of poverty. Some studies reveal that higher education plays a significant role in an equal society (Gregorio and Lee 2002). O'Neill (1995) found that education leads to a reduction in income inequality in developed countries at the cost of less developed countries. Breen and Chung (2015) provided evidence by conducting a simulation that increasing educational attainment and educational policy might mitigate or have a minor impact on inequality in the United States. On the other hand, a number of papers support the argument that education leads to higher income distribution. Microsimulations conducted on most Latin American countries also suggest that the increase in years of education in the 1990s and 2000s led to greater income inequality (Battistón et al. 2014). Glomm and Ravikumar (2003) suggested that better-quality public education widens the gap between the rich and the poor. However, a counterargument for this is provided by Sylwester (2002). The study finds that expenditure on public education appears to be associated with a decrease in the level of income inequality. Thus, the effect of education on income inequality remains ambiguous based on the settings, timeframe, methodology used, environment, and countries.

The empirical evidence also varies from country to country. Falaris (2008) found that, in Panama, higher education and experience tend to increase wage inequality. Budría and Pereira (2005) found that the country's education contributed to wage dispersion in Greece, Norway, and Italy. Budría and Moro-Egido (2008) found that higher education is associated with higher within-group wage inequality in Spain. Patrinos et al. (2009) found that the effect of education on salary increases within-group equality in most Latin American countries and decreases in most East Asian countries. Tansel and Bodur (2012) found that education positively impacted within-group and between-group inequality in Turkey, with the most impactful contribution being university education. A study on sixteen developed European countries finds that returns to investment in education (henceforth "returns to education") increased throughout the wage distribution scale, and schooling may have a positive impact on within-group wage inequality because the returns to education are greater the higher the education level is (Martins and Pereira 2004). Moreover, a study on Asian economies for the period from 1960 to 2015 reveals that all levels of education enrollment increased inequality

2 The countries with available data with over 40% shares are Russia (58.6%), South Africa (42%), Turkey (40.7%), and India (40.6%).

3 According to the World Bank (2023), the same figure of the GINI coefficient was recorded in 2021.

(Arshed et al. 2019). All in all, most of the previous research was conducted in the cases of European countries, Latin American countries, and other developed countries. Fewer studies have paid attention to Asian countries and developing Southeast Asian countries like Thailand. To the best of our knowledge, there is not much research on this topic in Thailand.

This research investigates how the returns to each level of education contributed to wage inequality in Thailand between 2009 and 2018. The method of analysis consists of ordinary least squares and quantile regression. We estimate the Mincerian wage equation for individuals aged between 15 and 75 living in the central region of Thailand with recorded positive income. In the estimation process, education dummies are used instead of years of schooling due to the fact that the analysis using years of schooling will implicitly assume that the impact is constant across education levels. The education levels can be roughly classified into five groups: primary or less, lower secondary (middle school), upper secondary (high school), vocational, and tertiary (university) education. The main findings suggest that both within-group and between-group inequality is high in Thailand. The within-group inequality is the highest among university graduates and smallest among those with primary or less schooling. Education has a positive impact on returns to each level of education and income inequality. This effect became larger in magnitude as more years of education were pursued. Within-group and between-group inequality decreased during the period of study, especially around the middle of the wage distribution scale. The reason for this decline can be explained by the sudden changes in the minimum wage policy that was announced in 2011.

The rest of the paper is constructed as follows: Section 2 gives a background on Thailand's educational system and some issues regarding returns on education in Thailand. The methodology and a quantile regression model are provided in Section 3. Section 4 presents a data description, summary statistics, and a brief look at education distribution in Thailand and its evolution over time. Section 5 discusses the estimation results. Lastly, a discussion of the results and conclusion are given in Section 6.

2. Background on Thailand's Education System

"Basic education" in Thailand consists of six years of elementary education and six years of secondary education. Out of these 12 years of basic education, only nine years[4] are mandatory. However, the average duration of schooling in Thailand is still lower than the mandatory nine years, ranging from 7.9 to 8.8 years. The gender gap in schooling in Thailand has been shown to be narrowing since the 1990s (Knodel 1997). The adult literacy rate for Thailand is moderately high, averaging 93.77% and continues to increase over time. Between 2000 and 2018, the adult literacy rate for males remained at 95%, whereas for females, the ratio slightly increased from 91% to 92% during the same period, according to the World Bank. Apart from the number of children attending schools, the quality of teaching and education is also an important factor to consider.

Even though Thailand claims that basic education from pre-primary to high school is free of charge, schools that are actually free are few. Besides, the quality of those schools seems to be relatively deficient compared to those that require enrollment fees. The quality of education and the subsequent return received by university students are also vastly different. Consequently, those who graduate from top universities receive higher pay than those who do not. The problems students

4 These nine years are comprised of six years of elementary school and three years of lower secondary school.

encounter in higher education are a result of the quality of lower or basic education they receive. The PISA 2009 revealed that among three categories — reading, mathematics, and science assessment — Thailand ranked from 47th to 52nd among 65 countries. Even ten years later, the scores had not improved; PISA 2018 revealed that Thailand ranked 66th among 79 countries.

In addition, there are some issues regarding the returns on education in Thailand. Lathapipat (2008) found that between 1986-2006 the wages of high school graduates increased at a slower rate than those who had just graduated from primary school. The reason is that labor-intensive industries, such as food processing, tend to employ workers with only a primary school level of education or foreign laborers from Burma, whereas high-technology industries demand university graduates. Warunsiri and McNown (2010) found that the overall rate of returns to education in Thailand is between 14% and 16% by using the pseudo-panel estimation method on Thailand's National Labor Force Survey of workers born between 1946 and 1967. They also confirmed that workers in urban areas receive greater returns from education than rural workers. Surprisingly, returns on education for females appear to be greater than for males. This finding strengthens the argument for putting more emphasis on schooling for girls.

3. Methodology

The results from the Ordinary Least Square (OLS) method are computed based on the mean conditional distribution of the dependent variable, and it assumes that the marginal impact of education is constant over the distribution line. Thus, it may not be the best fit for some analyses when the data is not equally distributed. Quantile regression allows for the investigation into the different points of the conditional distribution of the dependent variable. The quantile regression used in this study was first introduced by Koenker and Bassett (1978). In the context of the wage equation, the quantile regression model can be written as:

$$lnw_{it} = X_{it}\beta_{\theta} + e_{\theta i} \text{ with } Quant_{\theta}(lnw_i \mid X_{it}) = X_{it}\beta_{\theta}, \tag{1}$$

where X_{it} is the vector of exogenous variables including age, age squared, gender dummies, education dummies, marital status, geographic location, firm size, industry, etc. Subscript t is the survey year. β_{θ} is the vector of parameters. $Quant_{\theta}(lnw_{it} \mid X_{it})$ denotes the θth conditional quantile of $ln\ w$ given X.
The θth regression quantile, $0<\theta<1$, is defined as a solution to the problem:

$$\underset{\beta \epsilon R^k}{Min}\left\{\sum_{i:y_i \geq x_i\beta} \theta |\ln w_{it} - X_{it}\beta_{\theta}| + \sum_{i:y_i < x_i\beta} (1-\theta)|\ln w_{it} - X_{it}\beta_{\theta}|\right\}, \tag{2}$$

which can also be written as:

$$\underset{\beta \epsilon R^k}{Min}\left\{\sum \rho_{\theta}(lnW - X_{it}\beta_{\theta})\right\}, \tag{3}$$

where ρ_{θ} is the checkpoint function defined as $\rho_{\theta}(z)=\theta z$ if $z \geq 0$ or $\rho_{\theta}(z)=(\theta-1)z$ if $z<0$. The linear programming method is used to solve the problem. The quantile regression minimizes an asymmetrically weighted sum of absolute errors. Standard errors for the estimated coefficients are derived using the Buchinsky (1994) bootstrap method. Unlike the OLS, the quantile regression estimates the returns to education at different points in the distribution of individuals in the same group. Furthermore, an additional level of education will be reflected not only as a shift in conditional wage distribution but also in the shape of the distribution.

4. Data Description

This study is based on the data from the survey conducted by the National Statistic Organization of Thailand (NSO). The data, ranging over the ten years period from 2009 to 2018, covers individuals aged between 15 and 75 who are living in central Thailand, including the capital, Bangkok. The 10-year samples in the study are composed of 181,123 samples in total. For cross-section analysis, the number of samples in 2009 and 2018 are 19,059 and 17,479, respectively. In the analysis, every individual works in the formal group. The informal group is excluded because of the lack of income or wage reports. The same reasoning also applied to the exclusion of self-employment. A firm with more than 100 employees is classified as a large firm. The industry and occupation of individuals in the samples are also included, but not shown in the results. Other dummy variables include being female, being a household head, being married, and living in Bangkok, as opposed to in the central region outside Bangkok. Individuals in the samples are classified according to their highest educational attainment at the time of the interview. The study focuses on five quantiles, including the 10th, 25th, 50th, 75th, and 90th. The distribution of individuals' education levels is shown in Table 1. Apart from the 5 quantiles from the main analysis, Table 1 also includes two more quantiles: the lowest 5th and the highest 95th for a simple descriptive analysis.

In addition, the hourly wage is calculated as follows. The total income includes wage, bonus, and overtime earnings. The total working hours from the survey are reported on a weekly basis. Bonuses are recorded as an annual income, while wages and overtime payments are monthly. Thus, a bonus is roughly divided by 52 to make a weekly bonus, while wage and overtime are multiplied by 7/30. Together with the weekly total working hours, we get the hourly wage.

Table 1 illustrates the wage and educational distribution and its evolution from 2009 to 2018. The first and second rows present the mean income and its standard deviation each year. In 2009, the mean income was 45.21 Baht per hour and continued to increase over time to 68.49 Baht per hour in 2018, recorded as a 51.50% increase. The hourly wage in each quantile also increased over time. The most noticeable increase in hourly wage is found in the lowest quantile (q5), which doubled in value throughout the study. On the contrary, the smallest increase is seen on the highest quantile (q95) at a 34.57% increase. The wage ratios between quantiles are a simple tool for measuring wage inequality overall. The wage ratios indicate a decrease in wage inequality between the top and bottom of the wage distribution range, especially between the highest and the lowest quantile.

The educational distribution is shown at the bottom part of Table 1. There was a decrease in the number of primary school graduates. The number dropped by 12.23%. Meanwhile, from 2009 to 2018, the percentage of higher education graduates increased. The number of high school graduates increased the most during the period of study, followed by the number of university graduates. The number is recorded at 13.86% and 11.76%, respectively. The changes in educational distribution in Thailand between 2009 and 2018 suggest that more and more people have become more educated over the period.

Table 1. Summary Statistics for Wage Inequality and Educational Distribution from 2009 to 2018

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Change 2018-2009 (%)
Mean	45.21	47.20	48.32	58.84	62.59	66.14	66.31	67.00	67.13	68.49	51.50
SD	51.97	85.30	53.65	93.47	68.01	77.36	66.45	68.42	64.15	65.19	-
Quantiles											
q5	14.38	15.00	16.67	18.67	21.49	24.31	25.46	27.50	26.25	29.17	102.90
q10	17.50	18.67	20.00	22.22	25.36	29.17	31.34	33.33	33.33	34.65	98.00
q25	23.33	24.31	25.28	29.17	35.42	37.92	37.92	37.92	38.89	40.44	73.33
q50	31.11	31.82	34.03	38.89	43.75	46.18	47.42	48.61	48.61	50.56	62.50
q75	47.40	47.64	48.61	58.33	64.82	68.06	72.92	72.92	72.92	72.92	53.85
q90	81.67	80.00	87.50	102.08	108.68	116.67	116.67	113.33	116.67	116.67	42.86
q95	121.38	121.53	133.33	152.70	159.31	170.14	160.42	166.67	159.67	163.33	34.57
Wage ratios											
q95/q5	8.44	8.10	8.00	8.18	7.41	7.00	6.30	6.06	6.08	5.60	-33.68
q95/q75	2.56	2.55	2.74	2.62	2.46	2.50	2.20	2.29	2.19	2.24	-12.53
q95/q50	3.90	3.82	3.92	3.93	3.64	3.68	3.38	3.43	3.28	3.23	-17.19
q50/q5	2.16	2.12	2.04	2.08	2.04	1.90	1.86	1.77	1.85	1.73	-19.91
Educational distribution (%)											
Primary	43.73	44.54	43.35	41.31	40.83	41.67	40.83	39.77	39.1	38.38	-12.23
Middle School	19.34	19.22	20.02	19.09	19.6	19.46	19.35	19.4	19.69	20.44	5.69
High School	11.69	11.71	11.81	12.28	12.05	12.08	13.6	13.79	13.75	13.31	13.86
Vocational	11.13	11.07	10.64	11.76	11.5	11.21	11.35	11.58	11.62	12.11	8.81
University	14.11	13.46	14.18	15.56	16	15.59	14.88	15.46	15.84	15.77	11.76
Number of Observations	19,059	18,750	18,321	18,525	18,445	17,506	17,324	17,681	18,033	17,479	

Source: Author's calculations

5. Estimation Results

Table 2 presents the OLS and quantile estimates for the 10-year data. The OLS and quantile results are all statistically significant at the 1 percent level. For the OLS results, those who are older, married, a household head, living in Bangkok, and working for a large company earn relatively more. Females earn relatively less than their male counterparts. The reference group for education dummies is primary school or lower. As expected, the returns to university education are the highest relative to other education categories, and the lowest beneficiaries are middle school graduates. Quantile regression gives results similar to those of OLS. In every quantile, those who are older, male, a household head, married, living in Bangkok, and working for a large company earn relatively more. When comparing the results at different quantiles, age and firm size seem to matter less when moving up along the conditional wage distribution. This trend suggests that the wage earners of the top quantile seem to be younger. On the contrary, those who are male, married, and are a household head seem to earn relatively more at higher quantiles. Meanwhile, living in the capital (Bangkok) is only advantageous to those located at both ends of the wage distribution scale.

The educational categories are presented at the bottom of Table 2. We conducted ANOVA to evaluate the difference at each point of the quantile. The results suggest that the quantile estimates at different points of the wage distribution are significantly different from one another at the 1 % level (the results are not included here). The returns for a university degree or higher are significantly higher than those of the lower educational levels. Moreover, the returns on education at different quantiles are as predicted. In every educational category, people in the higher quantiles receive a relatively higher income when compared to those in the lower quantiles, with a small erratic pattern spotted in the median (q50) of middle and high school graduates. In addition, note that the OLS estimates and median (q50) estimates are different. The OLS tends to underestimate the returns in every group. This underestimation is due to the fact that the OLS estimation is based on the mean conditional distribution of wages, where the majority of people are located at the lower end of the distribution scale. Overall, the returns on education favor university degree attainers, and in the top quantiles (q75 and q90), university degree holders receive more than double the salary of vocational college graduates.

(1) Cross-sectional Analysis of the Evolution of Educational Distribution

In this section, special attention is paid to the changes in returns to education between 2009 and 2018. Table 3 shows the OLS and quantile estimates of the Mincerian wage equation for 2009 and 2018. All coefficients are statistically significant at the 1% level. Overall, the results are in line with Table 2. In both years, those who are old, a household head, male, married, living in the capital (Bangkok), and working for a large company receive higher incomes than their respective counterparts. The trend over conditional wage distribution is also consistent with the results from Table 2. Firstly, age becomes less important at a higher quantile. Secondly, there is no clear relation between the location of employment and placement within the wage distribution scale. Lastly, being a married male household head plays a more important role at higher quantiles. Furthermore, over the 10-year period, the coefficients for age, household head, gender, marital status, regional dummies, and firm size have become smaller in magnitude, except for the coefficient for ‘living in Bangkok’ at the top quantile (q90). This could be because the difference within these characteristic groups has become smaller over time, leading to less inequality among individuals.

Table 2. Quantile and OLS Estimates for Wage Earners between 2009 and 2018

	Dependent variable: ln wage					
	OLS	q10	q25	q50	q75	q90
Age	0.035***	0.035***	0.028***	0.028***	0.028***	0.031***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Age squared	-0.0004***	-0.0004***	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Household Head	0.060***	0.042***	0.041***	0.048***	0.061***	0.077***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)
Female	-0.153***	-0.105***	-0.104***	-0.126***	-0.157***	-0.190***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
Married	0.066***	0.045***	0.043***	0.053***	0.069***	0.084***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Living in the Capital	0.262***	0.237***	0.214***	0.223***	0.239***	0.259***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)
Large firm	0.202***	0.232***	0.180***	0.158***	0.159***	0.173***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.005)
Grade: Middle School	0.161***	0.111***	0.103***	0.127***	0.157***	0.186***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
Grade: High School	0.255***	0.162***	0.168***	0.213***	0.270***	0.317***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)
Grade: Vocational	0.454***	0.281***	0.315***	0.400***	0.499***	0.595***
	(0.004)	(0.005)	(0.004)	(0.003)	(0.005)	(0.008)
Grade: University	0.966***	0.669***	0.757***	0.911***	1.095***	1.257***
	(0.003)	(0.006)	(0.004)	(0.005)	(0.005)	(0.008)
Constant	2.246***	1.871***	2.210***	2.426***	2.611***	2.769***
	(0.011)	(0.015)	(0.011)	(0.010)	(0.011)	(0.019)
Observations	181,123	181,123	181,123	181,123	181,123	181,123

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3. OLS and Quantile Regression Estimates of the Wage Equations, 2009 and 2018

	OLS	q10	q25	q50	q75	q90
Year 2009						
Age	0.046***	0.044***	0.041***	0.039***	0.038***	0.042***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Age squared	-0.0005***	-0.001***	-0.0005***	-0.0004***	-0.0004***	-0.0004***
	(0.00002)	(0.00003)	(0.00003)	(0.00002)	(0.00003)	(0.00004)
Household Head	0.068***	0.047***	0.045***	0.053***	0.077***	0.103***
	(0.007)	(0.011)	(0.008)	(0.007)	(0.009)	(0.013)
Female	-0.165***	-0.103***	-0.110***	-0.146***	-0.177***	-0.210***
	(0.007)	(0.011)	(0.007)	(0.007)	(0.008)	(0.012)
Married	0.065***	0.053***	0.039***	0.051***	0.068***	0.084***
	(0.007)	(0.010)	(0.007)	(0.007)	(0.009)	(0.012)
Living in the Capital	0.304***	0.308***	0.283***	0.266***	0.257***	0.286***
	(0.009)	(0.014)	(0.009)	(0.009)	(0.009)	(0.015)
Large firm	0.228***	0.269***	0.210***	0.195***	0.197***	0.185***
	(0.008)	(0.011)	(0.008)	(0.008)	(0.010)	(0.014)
Constant	1.991***	1.749***	1.983***	2.180***	2.337***	2.456***
	(0.035)	(0.053)	(0.035)	(0.035)	(0.041)	(0.059)
Observations	19,059	19,059	19,059	19,059	19,059	19,059
Year 2018						
Age	0.031***	0.031***	0.025***	0.025***	0.025***	0.026***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)
Age squared	-0.0003***	-0.0004***	-0.0003***	-0.0003***	-0.0002***	-0.0002***
	(0.00002)	(0.00003)	(0.00002)	(0.00002)	(0.00002)	(0.00003)
Household Head	0.058***	0.046***	0.041***	0.043***	0.043***	0.063***
	(0.006)	(0.007)	(0.005)	(0.005)	(0.006)	(0.011)
Female	-0.128***	-0.086***	-0.081***	-0.107***	-0.135***	-0.161***
	(0.006)	(0.007)	(0.005)	(0.005)	(0.006)	(0.011)
Married	0.056***	0.024***	0.033***	0.040***	0.060***	0.082***
	(0.006)	(0.007)	(0.005)	(0.005)	(0.006)	(0.011)
Living in the Capital	0.247***	0.202***	0.186***	0.213***	0.256***	0.293***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.010)	(0.014)
Large firm	0.163***	0.189***	0.139***	0.129***	0.126***	0.129***
	(0.007)	(0.008)	(0.007)	(0.006)	(0.008)	(0.014)
Constant	2.761***	2.497***	2.812***	2.941***	3.069***	3.168***
	(0.030)	(0.044)	(0.031)	(0.023)	(0.031)	(0.055)
Observations	17,479	17,479	17,479	17,479	17,479	17,479

Table 4. OLS and Quantile Regression Estimates for Educational Categories, 2009 and 2018

	OLS	q10	q25	q50	q75	q90
Year 2009						
Grade: Middle School	0.192***	0.125***	0.135***	0.152***	0.189***	0.228***
	(0.010)	(0.015)	(0.010)	(0.010)	(0.012)	(0.017)
Grade: High School	0.272***	0.152***	0.183***	0.246***	0.304***	0.366***
	(0.012)	(0.017)	(0.012)	(0.012)	(0.014)	(0.020)
Grade: Vocational	0.508***	0.329***	0.385***	0.459***	0.557***	0.593***
	(0.012)	(0.018)	(0.012)	(0.012)	(0.014)	(0.027)
Grade: University or Higher	1.033***	0.736***	0.821***	0.987***	1.171***	1.356***
	(0.012)	(0.018)	(0.012)	(0.012)	(0.014)	(0.020)
Year 2018						
Grade: Middle School	0.146***	0.089***	0.084***	0.115***	0.143***	0.228***
	(0.008)	(0.010)	(0.006)	(0.007)	(0.008)	(0.017)
Grade: High School	0.220***	0.133***	0.140***	0.193***	0.232***	0.364***
	(0.010)	(0.009)	(0.008)	(0.008)	(0.010)	(0.020)
Grade: Vocational	0.418***	0.232***	0.279***	0.369***	0.463***	0.652***
	(0.010)	(0.010)	(0.010)	(0.009)	(0.013)	(0.020)
Grade: University or Higher	0.902***	0.607***	0.710***	0.853***	0.988***	1.357***
	(0.010)	(0.014)	(0.011)	(0.011)	(0.014)	(0.020)

Note: *p<0.1; **p<0.05; ***p<0.01

Next, we examine the returns for different levels of education for 2009 and 2018 separately. Table 4 shows the OLS and quantile regression results for each education level in 2009 and 2018. The reference group is primary or less schooling. The coefficients for the returns for schooling are all positive and statistically significant at 1% for both years. University degree holders still receive relatively higher returns than other education categories. The coefficients of every education level become larger in magnitude at higher quantiles. Similar to other characteristics, education estimates become smaller in magnitude between 2009 and 2018. This indicates that the inequality among individuals at the same level of education has become smaller over the period of study. However, the difference between education levels indicates a positive contribution of education to inequality. In addition, the deviation of the OLS estimates from the median quantile estimates indicates that the returns for each level of education are not uniformly distributed in the labor market. Table 5 illustrates the q75-q25 and q90-q10 spreads for 2009 and 2018. In general, the q90-q10 spreads are larger than the q75-q25 spreads. This means that inequality is more prevalent at both ends of the wage distribution scale. As for the individual characteristic factors, inequality as a result of age is not evident in Thailand during the period of study. Secondly, the income gap between the household heads at both ends of the distribution scale has become smaller. In 2018, the q90-q10 spreads for married individuals and those who live in Bangkok as opposed to the central area have become significantly wider compared to 2009. Next, the disadvantage of being a female has become less apparent, indicated by a smaller negative value between 2009 and 2018. Lastly, the income gap between individuals working for a large company (>100 employers) has become more noticeable. This finding is in line with Falaris (2008) in Panama and Schaffner (1998) in Peru, who found a declining firm-size effect, and Machado and Mata (2001) in Portugal, who found an increasing firm-size effect across the wage distribution scale.

(2) Changes in Within-group Wage Inequality

The spreads for education levels are presented at the bottom part of Table 5. The q75-q25 and q90-q10 spreads are simple and effective tools for analyzing changes in within-group wage inequality. The within-group wage inequality is highest for those with a university degree or higher, followed by vocational education and high schoolers, and is the lowest for those with primary or less education. We observe some distinctive patterns regarding the contribution of education to inequality. In 2009, the q90-q10 spreads for all education levels were double those of the q75-q25 spreads. In 2018, the differences between the q90-q10 and the q75-q25 spreads had become even more pronounced, ranging from 2.2 to 2.6 times higher than the 2009 data. This indicates that the wage dispersion has become even more concentrated at both ends of the wage distribution scale during this time.

Table 5. Measure of Dispersion

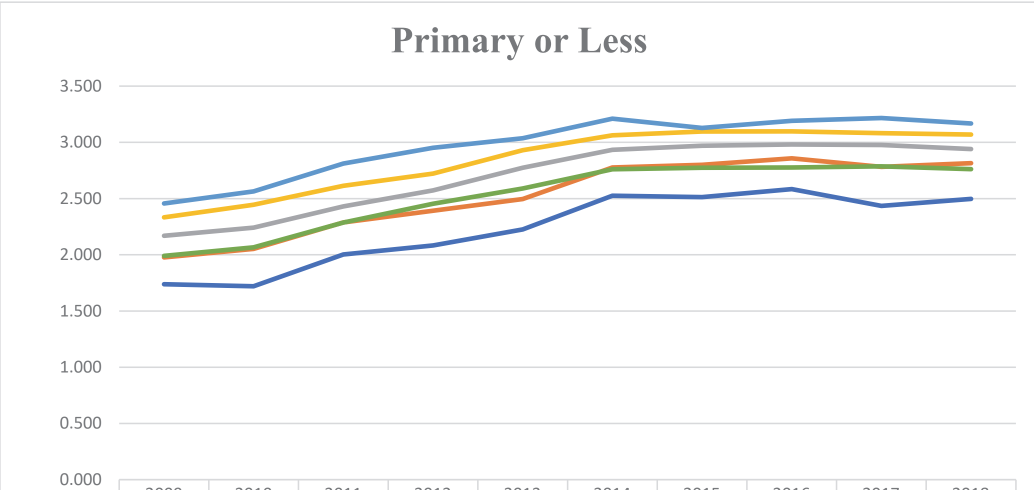
	2009		**2018**		**Change**
	q75-q25	q90-q10	q75-q25	q90-q10	Δ(q90-q10)
Age	-0.7	-0.2	0	-0.5	-0.3
Household Head	3.2	5.6	0.2	1.7	-3.9
Female	-6.7	-10.7	-5.4	-7.5	3.2
Married	2.5	3.2	2.7	5.8	2.6
Living in Bangkok	2.9	3.1	7	9.1	6
Large firm	-1.3	-8.4	-1.3	-6.0	2.4
Education level					
Primary or less	35.73	71.83	25.48	67.11	-4.71
Middle school	41.12	82.20	31.34	76.34	-5.86
High school	47.80	93.06	34.68	83.07	-9.99
Vocational	52.96	104.11	43.92	98.43	-5.68
University	70.73	133.89	53.27	121.05	-12.84

Note: The differentials are multiplied by 100.
Source: Author's calculation based on the estimation results in Table 3 and Table 4

Over time, the within-group wage inequality changes. The income gap between the 10th percentile and 90th percentile (q90-q10 spread) in each education category becomes slightly smaller, which contradicts the evidence from Turkey provided by Tansel and Bodur (2012), who observed increases in the wage gap in all education categories. However, the finding is in line with that of Girma and Kedir (2003), who found declining returns on wage distribution at all levels of education in Ethiopia. Over the10-year period, the largest decrease in the q90-q10 spread can be found among those with a university degree, followed by secondary education (high school). The smallest change is seen in primary or less schooling. On the contrary, the differentials between the 75th and 25th quantiles (q75-q25 spreads) decreased substantially during the period of study. This indicates that the wage differentials become smaller (flatter) around the middle of the income distribution, but the differences between both ends of the distribution scale remain relatively the same. Overall, within-group inequality has decreased for every education category, with most of the contribution coming from the declines between the middle q75-q25 spreads. The finding is comparable to that of Abadie (1997), who found a reduction in within-group inequality in Spain.

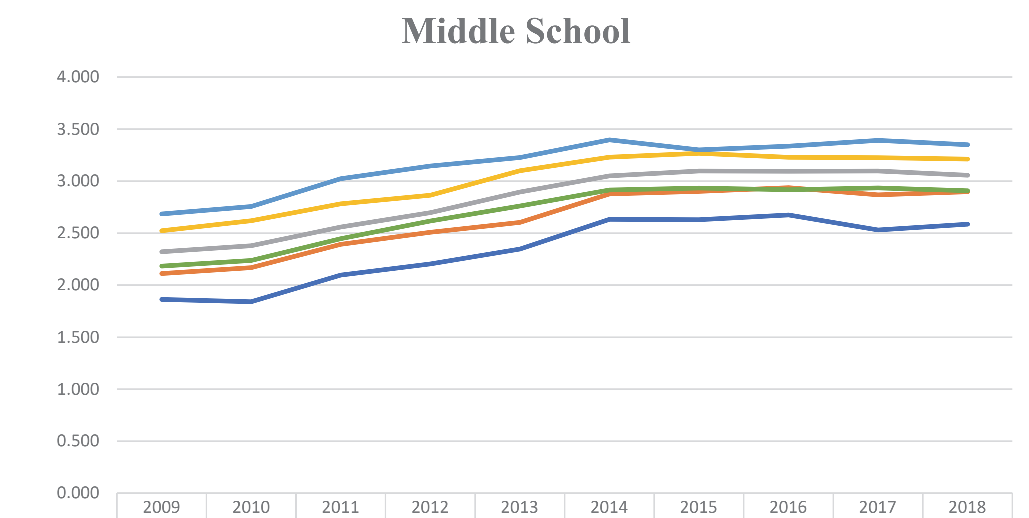
The differences in the returns for each level of education compared to the returns on primary education have become smaller in every category, indicating that between-group wage inequality in Thailand has improved. The wage gap between those with primary or less and those with university or higher schooling has become smaller over time. The difference in q90-q10 spreads between the two education categories has become smaller mostly due to the drop in return for having a university degree. However, the gap is still very high compared to the situation in Turkey (Tansel and Bodur 2012). The income gap between a secondary degree and a university degree also dropped slightly due to the fact that the returns on a university or higher degree decreased more than those of a secondary degree. In conclusion, the between-group inequality between university level and other education levels was reduced from 2009 to 2018.

Figures 1 to 5 plot returns for each level of education for each quantile along with the OLS estimate from 2009 to 2018. The education levels are primary school or less, middle school, high school, vocational school, and university or higher, respectively. The five figures illustrate the changes in the quantile returns for each educational level each year. For primary school graduates, the OLS result, which estimates the result using the mean of conditional wage distribution, is leaning towards the q25. This indicates that there are more people at the bottom of the wage distribution scale relative to the top. Over time, the gap between q25 and q75 (q75-q25 spread), indicated by the orange and yellow lines, respectively, had become smaller. The gap between q10 and q90 (q90-q10 spread) was the smallest in 2015 and 2016 before widening again in the following year. Similarly, the results for middle and high school graduates shown in Figures 2 and 3 are comparable to the primary school



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
q10	1.738	1.720	2.002	2.083	2.225	2.525	2.513	2.584	2.435	2.497
q25	1.976	2.052	2.288	2.392	2.496	2.776	2.800	2.857	2.782	2.814
q50	2.168	2.241	2.430	2.573	2.773	2.933	2.969	2.981	2.976	2.941
q75	2.333	2.445	2.612	2.721	2.929	3.062	3.096	3.097	3.081	3.069
q90	2.456	2.564	2.811	2.951	3.037	3.210	3.128	3.192	3.216	3.168
OLS	1.991	2.066	2.286	2.453	2.590	2.761	2.773	2.776	2.787	2.761

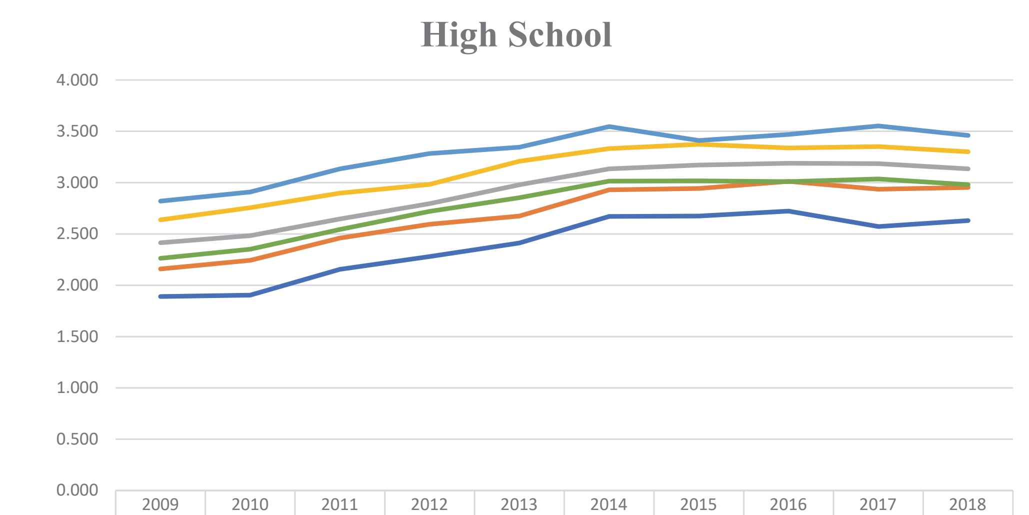
Figure 1. Returns to Education for Primary School Graduates or Lower from 2009 to 2018
Source: Author's calculation. Calculated using OLS and quantile regression results, excluding the intercept for each year separately. The log wage is regressed on a set of control variables, including age, age squared, gender dummies, education dummies, geographic location dummies, industry, firm size, marital status, and relation to the household head. The estimation results are shown in the table below the figure. The above figure plotted the OLS and quantile estimations for primary or lower educational levels for 2009-2018.



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
q10	1.862	1.840	2.096	2.204	2.347	2.633	2.628	2.675	2.530	2.586
q25	2.112	2.168	2.392	2.508	2.603	2.876	2.902	2.937	2.868	2.898
q50	2.321	2.379	2.559	2.697	2.896	3.051	3.098	3.095	3.097	3.056
q75	2.523	2.619	2.782	2.864	3.099	3.230	3.267	3.229	3.225	3.212
q90	2.684	2.756	3.023	3.144	3.227	3.396	3.301	3.337	3.391	3.349
OLS	2.183	2.237	2.446	2.617	2.760	2.915	2.933	2.917	2.935	2.907

Figure 2. Returns to Education for Middle School Graduates from 2009 to 2018

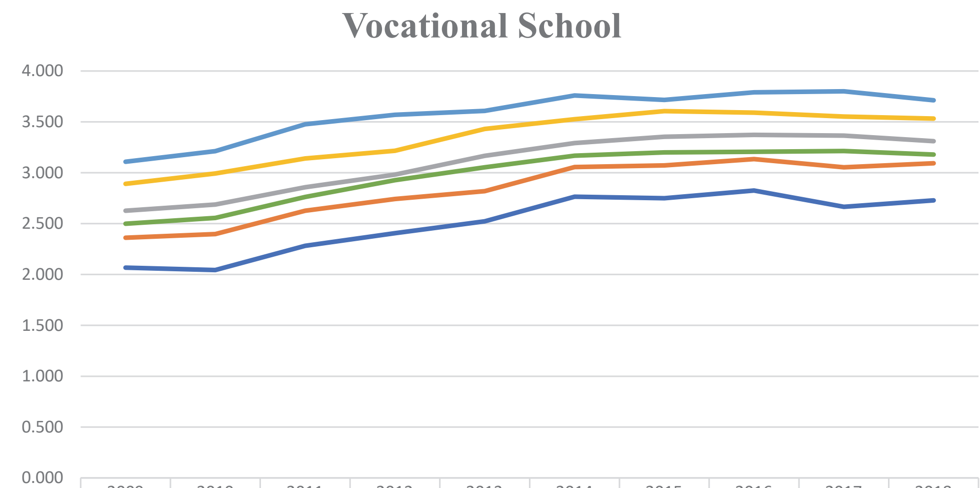
Source: Author's calculation. Calculated using OLS and quantile regression results, excluding the intercept for each year separately. The log wage is regressed on a set of control variables, including age, age squared, gender dummies, education dummies, geographic location dummies, industry, firm size, marital status, and relation to the household head. The estimation results are shown in the table below the figure. The above figure plotted the OLS and quantile estimations for middle school educational level for 2009-2018.



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
q10	1.890	1.904	2.156	2.279	2.412	2.671	2.675	2.723	2.572	2.630
q25	2.159	2.244	2.460	2.594	2.674	2.930	2.944	3.013	2.936	2.954
q50	2.414	2.483	2.646	2.794	2.980	3.135	3.171	3.189	3.185	3.134
q75	2.637	2.756	2.898	2.984	3.209	3.333	3.373	3.338	3.351	3.301
q90	2.820	2.909	3.135	3.283	3.345	3.546	3.411	3.471	3.553	3.461
OLS	2.263	2.352	2.544	2.720	2.853	3.014	3.016	3.010	3.036	2.981

Figure 3. Returns to Education for High School Graduates from 2009 to 2018

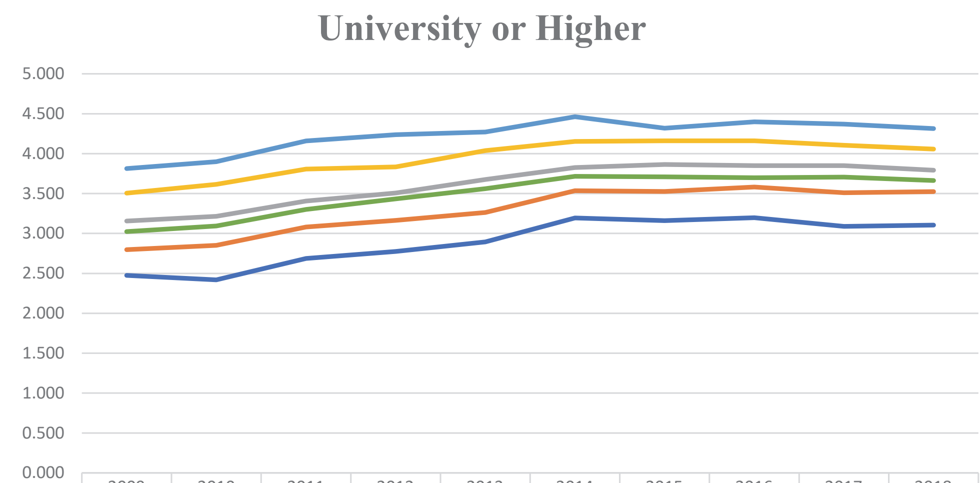
Source: Author's calculation. Calculated using OLS and quantile regression results, excluding the intercept for each year separately. The log wage is regressed on a set of control variables, including age, age squared, gender dummies, education dummies, geographic location dummies, industry, firm size, marital status, and relation to the household head. The estimation results are shown in the table below the figure. The above figure plotted the OLS and quantile estimations for high school educational level for 2009-2018.



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
q10	2.067	2.043	2.282	2.406	2.522	2.764	2.749	2.825	2.666	2.728
q25	2.361	2.396	2.628	2.742	2.819	3.056	3.072	3.134	3.053	3.093
q50	2.627	2.688	2.858	2.982	3.166	3.292	3.353	3.372	3.365	3.310
q75	2.890	2.992	3.140	3.216	3.431	3.526	3.605	3.592	3.553	3.533
q90	3.108	3.212	3.477	3.569	3.608	3.759	3.716	3.790	3.800	3.712
OLS	2.499	2.556	2.763	2.927	3.053	3.168	3.201	3.206	3.214	3.179

Figure 4. Returns to Education for Vocational School Graduates from 2009 to 2018

Source: Author's calculation. Calculated using OLS and quantile regression results, excluding the intercept for each year separately. The log wage is regressed on a set of control variables, including age, age squared, gender dummies, education dummies, geographic location dummies, industry, firm size, marital status, and relation to the household head. The estimation results are shown in the table below the figure. The above figure plotted the OLS and quantile estimations for vocational school educational level for 2009-2018.



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
q10	2.474	2.419	2.688	2.773	2.896	3.194	3.160	3.198	3.089	3.104
q25	2.797	2.852	3.081	3.163	3.263	3.536	3.527	3.582	3.511	3.525
q50	3.156	3.215	3.407	3.507	3.676	3.825	3.864	3.851	3.850	3.794
q75	3.505	3.614	3.807	3.834	4.038	4.153	4.162	4.161	4.106	4.057
q90	3.813	3.899	4.160	4.237	4.271	4.462	4.320	4.398	4.371	4.314
OLS	3.024	3.094	3.301	3.433	3.561	3.716	3.709	3.699	3.707	3.663

Figure 5. Returns to Education for University Graduates or Higher from 2009 to 2018

Source: Author's calculation. Calculated using OLS and quantile regression results, excluding the intercept for each year separately. The log wage is regressed on a set of control variables, including age, age squared, gender dummies, education dummies, geographic location dummies, industry, firm size, marital status, and relation to the household head. The estimation results are shown in the table below the figure. The above figure plotted the OLS and quantile estimations for university or higher educational levels for 2009-2018.

graduates, with the OLS line lying a little bit above the q25 line. In Figure 4, the returns for vocational school graduates exhibit a wider income gap between each quantile in general compared to the former three categories.

The OLS estimate lies between the q25 and q50 lines, indicating that people are moving up the conditional wage distribution scale as their education level becomes higher. The q75-q25 gap has become a little bit smaller over time, while the q90-q10 gap seems relatively unchanged. The q90-q10 gap was the largest in 2017. The returns for university graduates, shown in Figure 5, converge at the end of the timeline. The q75-q25 spread has presented a shrinking trend since 2014, and so has the q90-q10 spread. The income gap between the top and bottom quantiles was the smallest in 2015.

6. Discussion and Conclusion of the Results

This study explores the connection between educational attainment and wage inequality in Thailand from 2009 to 2018, using the OLS and quantile regression analysis. The log hourly wage is regressed on the individual characteristics and education dummies, which are classified into five categories: primary or less, middle school, secondary or high school, vocational school, and university or higher. The main results suggest the following. Firstly, both within-group and between-group inequality in Thailand is high throughout the period of study. Secondly, education positively contributes to increasing income inequality, and the effects become greater at the higher education level. Thirdly, the analysis captures a slight decline in the within-group inequality between the top (q90) quantile and the bottom (q10) quantile and a moderate reduction in the income gap within the same education levels between the middle (q75-q25) quantiles. Fourthly, the between-group inequality appeared to manifest a decreasing trend from 2009 to 2018. Similar to the within-group inequality, a reduction occurs mostly around the middle of the wage distribution scale. Lastly, university graduates experienced the largest negative changes in income inequality compared to other education categories. The changes are mainly caused by the fact that wages rose at a higher rate at the lower quantiles (q10 and q25) than wages at the higher quantiles (q75 and q90). From Figure 5, the 10-year changes in the returns to university graduates at the 10th and 25th quantiles are 0.63 and 0.72, respectively. Meanwhile, the changes over 2009-2018 at the 75th and 90th quantiles for university degree holders are 0.56 and 0.50, respectively. The same reasoning also applies to other education levels. Moreover, it is important to note that the results are applied to the central region of Thailand and not the whole country.

To explain these phenomena, we can take a look at the history of changes in Thailand’s wage policy. In 2011, there was a major change in Thailand’s minimum wage law (Lathapipat and Poggi 2016). The government launched a new policy stating that the wage rates in Thailand were to be increased by an average of 60%, from around 170-220 Baht per day prior to the changes to the minimum of 300 Baht per day, and this was to take effect from 2013 for the whole country. The spike came as a sudden adjustment and was the biggest change in the shortest timespan in Thailand’s history. This was intended to help the low-paid sectors, such as young and old workers and people with low education, who can also be considered to be located in the bottom half of the quantiles (Carpio et al. 2019). Furthermore, those with tertiary education also experienced some adjustment. In addition to the 300 Baht minimum wage law in 2011, the monthly payment for university graduates also increased to a minimum of 15000 Baht, compared to 8000-12000 Baht prior to the policy announcement. This immediately set the payments for university graduates at a higher rate than secondary and vocational degree holders, even for those with the same job. Thus, the wage premiums are expected to be the largest for bachelor's degree holders, as confirmed by Tangtipongkul (2015). This policy change targeted university graduates who are on the lower end of wage distribution. Hence, the changes in wage policy are the major causes for the smaller income gap in the 2010s. This fact is associated with the findings of this study.

Another explanation that could contribute to the changes in income inequality during this period is structural change or structural transformation. Structural change refers to a dramatic shift in industry-specific operations or sectoral activities brought about by economic growth and developments that lead to an increase in overall output. According to Warr and Suphannachart (2022), the period between 2000 and 2017 in Thailand witnessed a recovery from the Asian financial crisis and the global financial crisis. On the one hand, the changes in agricultural, manufacturing, and service shares to GDP and their respective growth are relatively stable during this period compared to the period before 2000. On the other hand, income inequality, measured by the GINI coefficient, showed a decreasing trend during the same period. Warr and Suphannachart (2022) defined the tension between structural change and income inequality during the 2000-2017 period as ambiguous, as described by the developer's dilemma or Kuznets' hypothesis. This period is characterized by weak growth-enhancing structural transformation and stable or declining inequality, suggesting an ambiguous relationship between the two.

One may argue that the results contradict the widely believed theory of skill-biased technical change (SBTC), which suggests a widening gap in income inequality between skilled and unskilled labor. However, skill-biased technical changes tend to prevail more in developed countries than in developing ones (Pi and Zhang 2018). Developing countries differ from developed ones in several respects. Firstly, in developing nations, goods markets operate with considerable openness, resulting in fixed prices for goods from both skilled and unskilled sectors. However, the capital market operates under financial regulations, leading to the endogenous determination of capital rental rates. Moreover, these countries often exhibit a dual economy, with a sizable rural sector alongside high unemployment rates in urban areas. Thus, when estimating how skill-biased technical changes (SBTC) affect income inequality in developing countries, one must take into account the differences in characteristics between countries. Furthermore, Behar (2013) proposes that technological changes do not always favor skilled workers; they can benefit either skilled or unskilled workers. Specifically, in the case of Thailand, Suphannachart (2019) found that technological change, measured by total factor productivity (TFP), lessens the gap in income inequality in the long run (1988-2017).

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