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Effects of Technological Change on Income Inequality in Thailand

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Abstract

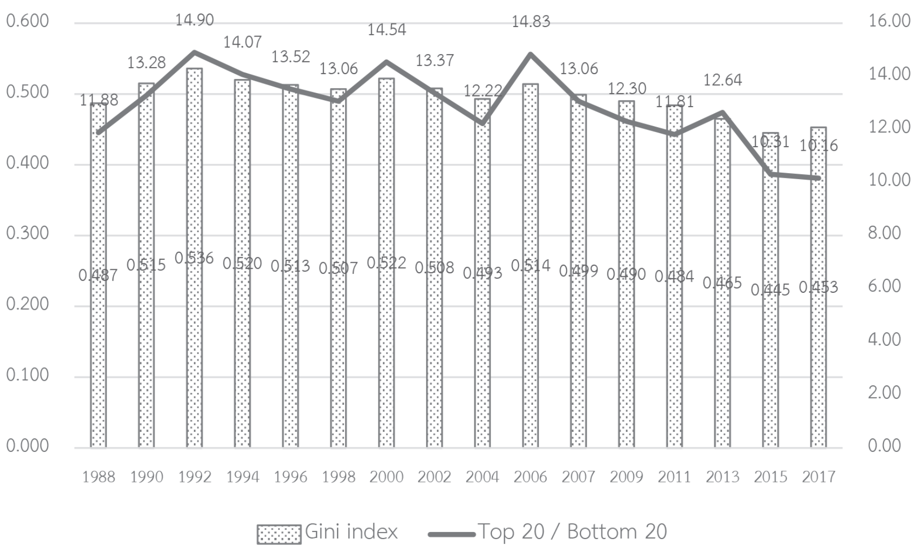
This paper examines the impact that technological change has on income inequality in Thailand. Total factor productivity (TFP) is measured as a proxy for technological progress while the Gini coefficient represents income inequality. Since income inequality is an issue that has lasted for several decades and tends to concentrate in certain areas, both national-level yearly data (1988-2017) and provincial-level panel data (76 provinces during 2009-2017) are employed using regression analysis. The results show that an increase in TFP reduces income inequality in the long run. Other factors that help in alleviating inequality are human capital, increasing income per capita, and declining agricultural GDP shares. In contrast, trade openness and FDI increase inequality. Additionally, the significance of spatial correlation among provinces implies that the policy should target groups of provinces in close proximity rather than focusing on various small areas.

Keywords: Income inequality, Regression analysis, Technological change, Total factor productivity, Thailand

Introduction

Over the past decades, the Thai economy has recorded relatively high economic growth rates, improving the living standard of Thai people. The poverty incidence has declined remarkably. However, income inequality has hardly improved and has caused detrimental effects on the Thai society in several respects, from illegal acts to social and political unrest. It is evident that Thailand has been stuck in this inequality trap for several decades. Despite a slight decline of income inequality in recent years the situation has hardly improved given the continuous economic growth over the past decades. As shown in Figure 1, the Gini coefficient based on income was 0.453 in 2017, which is roughly the same as in 1988 (0.487). A similar pattern can be found when considering the income distribution within quintiles. The richest 20 percent have received an income that is about 10 times higher than that of the poorest 20 percent for three decades.

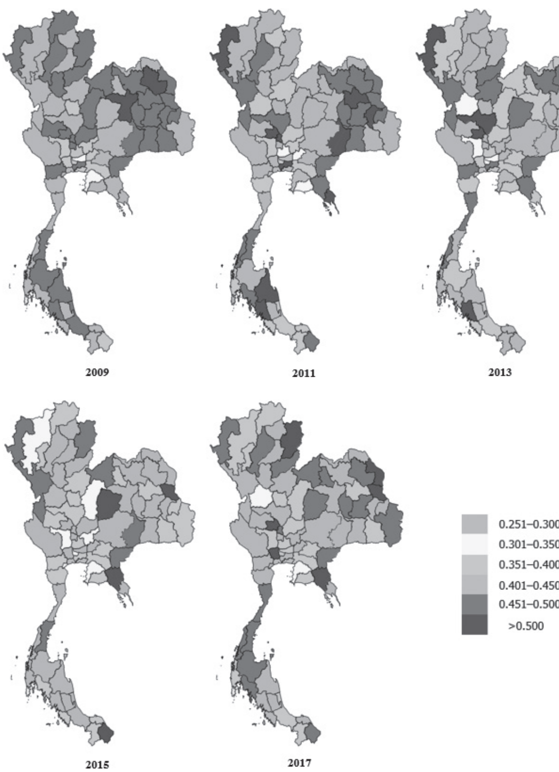
Figure 1. Income inequality in Thailand from 1988 to 2017



Source: National Economic and Social Development Board (NESDB)

Most of the low-income groups work in the informal sector, which requires relatively low-skilled workers, especially in the agricultural sector. They tend to concentrate in rural areas of the northeast, the north, and the southern border provinces of Thailand (NESDB, 2018). Similar levels of income inequality are also observed in provinces in close proximity (Figure 2). This suggests that location may affect inequality indexes or may correlate with the factors determining income inequality. Moreover, government policies promote specific investment zones with modern technology. Particularly, under the "Thailand 4.0" policy, special incentives are offered to attract hi-tech investments to locate in three provinces east of the capital, Bangkok. As infrastructure and technology development tend to be location specific, the expected prosperity might not be shared broadly.

Figure 2. Map of Thailand colored according to the Gini index, 2009-2017



Source: Author's depiction using NESDB data

Beyond the local context, the majority of previous studies confirm the important roles of globalization and technology as triggers of rising inequality in many developed countries (Acemoglu, 2003; Deskoska & Vlčková, 2018; Jaumotte, Lall, & Papageorgiou, 2013; Sequeira, Santos, & Ferreira-Lopes, 2017). It is possible that globalization and new technology will worsen the income disparity in Thailand as well (Jitsuchon, 2015). This inference is based on the fact that the Thai economy follows those of the US and other market-based economies and that the government policy (e.g. the policy for tax and infrastructure) largely favors investors or capitalists. Additionally, in this era of rapidly changing technology, most countries encounter challenges from robots, automation, computers, and other technological changes that tend to be skill biased.

Investigating the technology-inequality relation is definitely important for devising policy measures that can reduce the income disparity while preparing the country for the incoming technological advances. However, empirical evidence on the relationship between technological development and income inequality in Thailand is relatively scarce. Most of the related literature consists of cross-country studies or studies of specific foreign countries, and the results are quite mixed and inconclusive (Behar, 2016; Jaumotte et al., 2013; Kristal & Cohen, 2017; Santos, Sequeira, & Ferreira-Lopes, 2017; Sequeira et al., 2017). This issue is largely a matter of empirical study.

This paper is one of the first attempts to examine empirically the impact that technological change has on income inequality in Thailand, paying attention to both temporal and spatial dimensions. It applies econometric techniques to the income inequality determinant models. Since income inequality is an issue that has lasted for several decades and tends to be concentrated in particular locations, both national-level yearly data and provincial-level panel data are employed. The national-level model attempts to explain the chronic issue of the widening income gap over the past thirty years, whereas the provincial-level model investigates the role of spatial effects. The result is expected to shed light on policy recommendations at both the national and the provincial level.

The following section discusses the related literature. Section 3 describes the methods and data. The regression results are interpreted in Section 4 with emphasis on the technology–inequality relation. Finally, a conclusion is drawn.

2. Literature Review

There is a rich theoretical literature explaining the causes of inequality. However, there is no unified theory encompassing all the relevant aspects that explain inequality (Salverda, Nolan, & Smeeding, 2011). This section emphasizes the relationship between technological change and income inequality as well as other key factors affecting inequality at the country level.

According to the theory of skill-biased technological change (SBTC), technological change could worsen income inequality by reducing the demand for low-skill activities and increasing the premium for higher-skill activities and returns on capital (Acemoglu, 2002, 2003). Skill premiums increase due to two effects. First, the skill premium reflects the productivity difference between sectors. Second, with full capital mobility, factor price equalization requires capital to flow to the sector operating the new technology; thus, workers in the new technology sectors are endowed with more capital, which boosts their relative wages (Jaumotte et al., 2013; Sequeira et al., 2017).

Many studies argue that total factor productivity (TFP) can be considered as a crude measure of technological change (Abramovitz, 1956; Griliches, 1996; Schultz, 1953; Solow, 1957). TFP is recognized as a residual of output growth that is not explained by growth in conventional inputs (sometimes known as the "Solow residual"). It thus includes, but is not confined to, the effects of advances of knowledge or technological progress. Despite the criticisms of the measurement of TFP (Chen, 1997), the concept of TFP is widely applied in many empirical studies published over more than half a century.

Regarding the relationship between technological change and income inequality, empirical studies (mostly international cross-country, the US, and China) often measure technological change as TFP and shares of information and communication technology (ICT) as capital stock. Studies that used TFP as a proxy for technological change find both insignificant and positive impacts of TFP on income inequality (Sequeira et al., 2017; Xu & Ouyang, 2015), while studies that use ICT capital stock find positive relations (IMF, 2016; Jaumotte et al., 2013), and the impacts also depend on the types of ICT (Santos et al., 2017).

Besides technology, other major factors found in the related literature are economic growth, globalization, and human capital. The vast body of literature concentrates on the relationship between growth (income per capita) and income inequality. Kuznets was one of the first economists to speculate regarding such a relationship that inequality might first increase as a nation makes the transition from an agricultural economy to an industrial one (Perkins, Radelet, Lindauer, & Block, 2013). Many subsequent empirical studies test the inverted U-shape hypothesis of Kuznets (1955), and the results are mixed and inconclusive (Jin & Lee, 2017; Perkins et al., 2013; Rodríguez-Pose & Tselios, 2009).

Globalization is generally considered to be the main cause of income inequality, especially in developed countries (OECD, 2011). The impact of globalization on income distribution often operates through trade, foreign direct investment (FDI), and other offshore activities. Increased trade integration and FDI flows are associated with higher relative wages of skilled workers, thus contributing to greater inequality. However, the evidence is mixed: the estimated impacts on inequality are positive (Behar, 2016; Jin & Lee, 2017), negative (IMF, 2016; Jaumotte et al., 2013), and insignificant (Sequeira et al., 2017).

With regard to human capital, the theories and related literature report no consensus on the effects of educational attainment on income inequality. Education is generally regarded as one of the most powerful tools for reducing income inequality, as it increases the earning opportunities for the poor (World Bank, 2002). Nonetheless, education can also improve labor skills and stimulate SBTC, causing more inequality (Sequeira et al., 2017), or it may have no direct effect on income distribution (Spence, 1973). Additionally, human capital is sometimes measured using the human development index; for example, Sequeira et al. (2017) find that this measure has a positive and significant impact on income inequality. Regarding the relationship between educational inequality and income inequality, most theoretical analyses tend to report that the two factors are positively correlated (Rodríguez-Pose & Tselios, 2009).

In developing countries, economic transformation, characterized as a relative decline in the proportion of agricultural output and employment or a move away from the agricultural sector to industry, is expected to improve income distribution by increasing the income of low-earning groups. Similarly, an increase in agricultural productivity is expected to reduce income inequality by increasing the income of agricultural workers (Jaumotte et al., 2013). However, the related literature reports that the adoption of agricultural technology, which is a key component of agricultural productivity, can sometimes worsen income inequality (Ding, Meriluoto, Reed, Tao, & Wu, 2011).

Moreover, there are findings relating to the temporal and spatial dimensions of inequality. For the dimension of time, income inequality in one year tends to be correlated with that in the previous year. This is because changes in the distribution of income take place slowly, as people are often reluctant to change their job for psychological and institutional reasons, and income levels are often perpetuated from one generation to another by means of inheritance, cultural background, and the characteristics of the community (Jaumotte et al., 2013). In terms of the spatial dimension, income is likely to spill across locations through trade, transfer payments, network and social capital, and economic, technological, and information externalities (Rodríguez-Pose & Tselios, 2009). This suggests that the factors (economic, social, and institutional) explaining income inequality might be correlated with location.

Regarding the empirical studies of the technology–inequality relation in Thailand, no study as yet focuses on examining this issue. The majority of previous Thai studies concentrate on the growth–inequality nexus (mostly influenced by the Kuznets curve) and the roles of human capital and social and institutional factors (Jitsuchon, 2014; Krongkaew, 1985; Paweenawat & McNown, 2014; Preechametta, 2015). Generally, papers tend to report that the growth–inequality patterns are consistent with the Kuznets curve and that human capital and household characteristics play crucial roles in reducing the income inequality. Pootrakul (2013) also finds that agricultural research investment can significantly reduce the Gini coefficient while agricultural liberalization widens the wage gap between low-skilled and high-skilled labor (Warr, 2014).

3. Methods

This study estimates the income inequality determinant models using econometric methods. The models investigate the national level using time series data and the provincial level using panel data.

3.1 Income Inequality Determinant Models

The dependent variable is income inequality, measured as the Gini coefficient index. Although the Gini coefficient is heavily criticized for its data deficiency as it is calculated based on household surveys, which tend to underestimate the income of the richest people, it is the only data set that is available at both national and provincial level. The underestimated level of income inequality in Thailand should not significantly affect the regression analysis because the method emphasizes on the changing pattern rather than the level of Gini index.

The explanatory variables are selected from the literature review. Theories and empirical studies point to four main determinants of inequality: economic growth, human capital, technology, and globalization. Other factors, such as economic transformation, are also tested. Given the complexity of the relationship between income inequality and its determinants, it is difficult to predict the sign a priori, and the significance of the relationship is a matter of empirical study. In a stylized form, the model can be written as shown below:

$$Gini = f\left(Growth, TFP, TO, FDI, Hcap, ET\right) \quad (1)$$

where Gini is income inequality, Growth is income per capita, TFP is technological change, TO is trade openness, FDI is foreign direct investment, Hcap is human capital, and ET is economic transformation.

This study mainly uses TFP as a proxy for technological change. TFP is measured based on the Solow-type growth accounting method (due to data availability). It is the residual of output growth after subtracting the growth rate of primary factor inputs (labor and capital), weighted by their cost shares. To capture the level information, the measured rate of change of TFP is converted into TFP indexes. TFP indexes are calculated for both the overall economy (namely TFPall) and the agricultural sector (TFPag) to examine their individual impacts on the Gini index. Note that land input is not included in the TFP calculation, because a previous study (Suphannachart & Warr, 2012) shows that the land expansion has been exhausted since 1978; thus, it is not necessary to include land growth in the present study. Besides TFP, the technology factor is alternatively measured as ICT shares and the R&D intensity ratio.

3.2 Data Collection

The employed data consist of national-level yearly data from 1988 to 2017 (30 observations) and provincial-level panel data including 76 provinces for the years 2009, 2011, 2013, 2015, and 2017 (380 observations). The dependent variable (Gini coefficient index based on income) data, both annual and provincial, are from the National Economic and Social Development Board (NESDB). Since the Gini index has been published every two years, the missing yearly data are estimated by linear interpolation to maintain sufficient observations for the national model.

The definitions and data sources of the explanatory variables are summarized as follows. The data are collected at both the national and the provincial level unless otherwise stated.

(1) Growth is measured as income per capita (baht per person). The data are from the NESDB.

(2) Technological change is represented by four alternative variables:

(2.1) The TFP of all sectors (TFPall) is defined based on the growth accounting method explained earlier. At the national level, the TFP data are from the NESDB (the NESDB publishes only the yearly data). At the provincial level, the author calculates the TFP based on the same method and data sources as used by the NESDB. The output and capital stock data are obtained from the NESDB, and the labor data are from the National Statistical Office (NSO).

(2.2) The TFP of the agricultural sector (TFPag) follows the same method and data sources as in the case of the overall TFP.

(2.3) The ICT value-added share (ICT) is the shares of information and communication in the GDP. Due to data limitations, the ICT capital stock data are not available, so the GDP data are used instead. The data source is the NESDB.

(2.4) The R&D intensity ratio (R&D) is the shares of the total R&D expenditure in the GDP. Note that R&D data are not available at the provincial level. The data source is the National Research Council of Thailand.

(3) Trade openness (TO) is measured as the shares of total exports and imports in the GDP. Note that trade openness data are not available at the provincial level. The data are from the Ministry of Commerce.

(4) Foreign direct investment (FDI) is measured as the shares of net flows of FDI in the GDP. Note that FDI data are not available at the provincial level. The data are from the Bank of Thailand.

(5) Human capital is represented by three variables.

(5.1) The human development index (HDI) is a statistical composite index incorporating key dimensions of human development; GNI per capita, education, and health. The data are obtained from the United Nations Development Programme (UNDP), but only annual data are available.

(5.2) Educational attainment (Edu) is measured as the shares of the labor force with an upper-secondary education level, and the data are from the NSO. It is also measured as the mean years of schooling (School), and the data are obtained from the NESDB.

(5.3) Education inequality (EI) is measured as the ratio of the labor force with a primary education level or lower to the labor force with a university education level. The data are from the NSO.

(6) Economic transformation (ET) is measured as the shares of agricultural GDP (ET1) and employment (ET2). The data are from the NESDB and NSO.

3.3 Data Analysis

For the national-level model, the time series data are tested for their stationarity using the augmented Dickey–Fuller (ADF) test, and two estimation methods are employed consecutively. The first estimation method is OLS, which follows the IMF (2016) by lagging all the explanatory variables by one year to guard against the endogeneity problem. The second method is the error correction model (ECM) developed by Hendry (1995), which helps to avoid the possibility of estimating spurious relationships and endogeneity while capturing both short-run and long-run relationships. It is also flexible, allowing the data series to be integrated of different orders. Under the ECM, the dependent variable is expressed in terms of a rate of change or first differencing, and the lagged level of the dependent variable is included as one of the explanatory variables. The other explanatory variables can be expressed in terms of levels and rates of change with a one- or two-year lag (Athukorala & Sen, 2002). The ECM can be estimated by OLS. The full model incorporating all the lagged levels and rates of change variables is tested by dropping statistically insignificant lag terms using the standard testing procedure to obtain a parsimonious ECM.

For the provincial-level model, to test the existence of a spatial pattern in the technology–inequality relationship, the spatial regression method is employed. In the standard linear regression model, there are two types of spatial effects – spatial dependence and spatial heterogeneity – which can be incorporated in two ways (Anselin, 1999). First, the spatial effect or spatial dependence is included as an additional regressor in the form of a spatial lagged dependent variable and thus is called a spatial lag model. It is appropriate when the focus of interest is the assessment of the existence and strength of spatial interaction. Second, spatial heterogeneity is incorporated into the error structure, producing a spatial error model. This model is appropriate when the concern is to correct for the potential bias of spatial autocorrelation due to the use of spatial data that vary with location and are not homogeneous throughout the data set. This study employs both spatial models.

In the spatial lag model, the Gini index in one province is assumed to be spatially dependent on the Gini index in neighboring provinces and hence takes the following form:

$$Y = \rho WY + X\beta + \varepsilon \tag{2}$$

where Y and X are dependent and explanatory variables, $\boldsymbol{\rho}$ is the spatial dependence parameter, and **W** is an $n \times n$ standardized spatial weight matrix (where n is the number of observations). In this study, W is a 380×380 symmetric matrix, as the data include 76 provinces for a 5-year period. It reveals whether any pair of observations consists of neighbors sharing common borders (contiguity basis). For example, if province i and province j are neighbors, then $w_{ij} = 1$ or 0 otherwise.

In the spatial error model, the data collected for each province are assumed to be heterogeneous, as every location has a certain degree of uniqueness relative to other locations. That is, the nature of spatial data can influence the spatial dependency and hence the error term is spatially correlated. The model takes the following form:

$$Y = X\beta + \varepsilon; \varepsilon = W\varepsilon + u \tag{3}$$

where Y and X are dependent and explanatory variables, **λ** is the spatial error parameter, and **u** is an error term that satisfies the classical assumptions of independent identical distribution (i.i.d) with constant variance σ2. W is the spatial weight matrix.

For the estimation technique, the maximum likelihood estimation (MLE) is used. The reason for this is that, in the spatial lag model, OLS is biased and inconsistent due to the endogeneity problem, whereas, in the spatial error model, OLS is unbiased but inefficient due to the spatial autocorrelation in the error term.

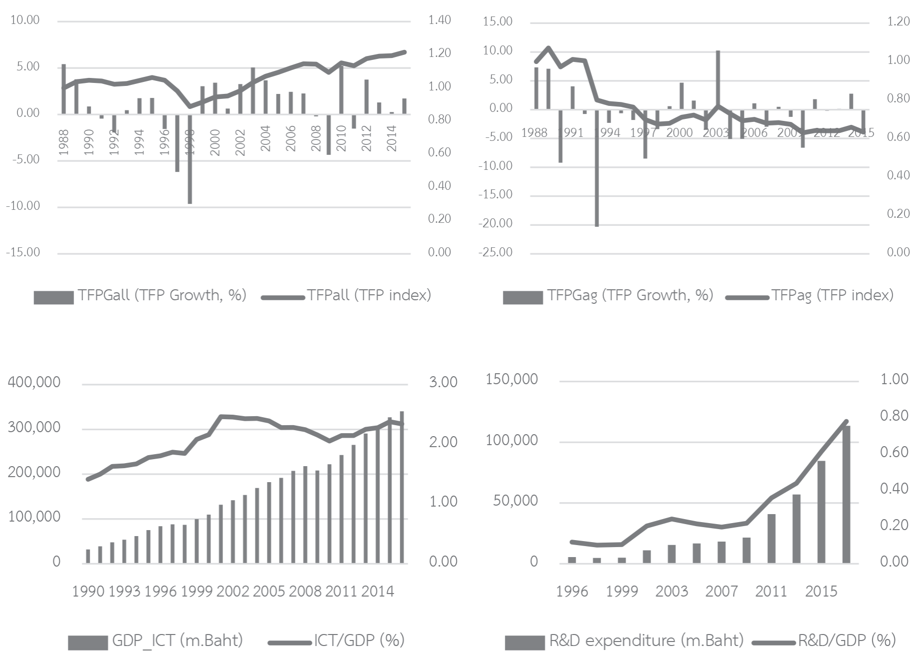
To test for the existence of a spatial pattern (Anselin, 1988), the Lagrange multiplier (LM) test is conducted. This is a test for the significance of spatial parameters. The null hypothesis is $\rho = 0$ under the spatial lag model and $\lambda = 0$ under the spatial error model. Under the null hypothesis, the test statistics have a chi-squared distribution with one degree of freedom. If the test statistic is greater than the critical value, the null hypothesis is rejected. The significance of the spatial parameters confirms the existence of spatial effects in the income inequality determinant model.

4. Results and Discussion

4.1 Background on the Overall Trends of Technological Change Indicators

This study measures the technological change using four indicators including the TFP of the overall economy (TFPall), the agricultural TFP TFPag), the ICT value added shares, and the R&D intensity ratios. They are briefly depicted in Figure 3. The overall TFP shows an increasing trend while that of the agricultural sector shows a declining trend. The ICT value added shares which is used as a proxy for the ICT capital stock shows a moderately increasing trend but such the trend tends to drop in recent years. The R&D intensity ratio, which is also considered as a main driver of the TFP growth, has recorded a remarkably upward trend. In overall, there has been an upward trend of technological progress in Thailand except in the agricultural sector. However, the levels of technological progress are quite small.

Figure 3. Trends of Technological Change Indicators in Thailand



Source: Author's calculation

4.2 Results from the National-Level Models: What the ECM Shows

According to the unit root test (Table 1), the annual data are a mixture of I(0) and I(1). As most data series are nonstationary, the ECM is more appropriate. Regarding the technology factor, the results for the national-level model indicate that the overall TFP (TFPall) is the only variable that is statistically significant, while the alternative measures, agricultural TFP, ICT, and R&D, are not significant. As for human capital, HDI turns out to be the only significant variable. The final parsimonious models comparing the results from OLS techniques following the IMF (2016) and the ECM following Hendry (1997) are shown in Table 2. Both results show that TFP has negative and significant impacts on the Gini index. However, as the ECM can guard against spurious regression and ensure valid t-statistics even in the presence of endogenous explanatory variables (Inder, 1993), only the ECM results are interpreted.

Table 1. Augmented Dickey-Fuller test for unit roots, 1988–2017

Variables	t-statistics for level without time trend	t-statistics for level with time trend	t-statistics for first difference without time trend	t-statistics for first difference with time trend
lnGini	0.056(0)	-3.187(0)	-3.433(0)	-4.991(3)
lnGrowth	-3.605(0)	-3.098(2)	-3.030(0)	-3.062(0)
lnTFPall	-0.908(0)	-2.190(1)	-4.330(0)	-4.312(0)
lnTFPag	-1.161(0)	-2.176(1)	-5.979(0)	-5.938(0)
lnICT	-2.695(2)	-3.464(8)	-3.447(1)	-3.752(1)
lnRD	0.156(1)	-1.671(1)	-2.959(0)	-3.301(0)
lnTO	-1.936(0)	-1.145(0)	-5.994(0)	-3.563(0)
lnFDI	-3.127(0)	-1.245(2)	-5.646(1)	-5.592(1)
lnHDI	-1.152(0)	-1.554(0)	-4.701(0)	-4.531(1)
lnSchool	-2.080(1)	0.596(1)	-1.503(1)	-4.743(0)
lnEdu	-1.813(2)	-1.352(0)	-5.287(0)	-5.426(1)
lnEI	0.359(0)	-3.248(0)	-5.584(0)	-5.450(0)
lnET1	-2.678(0)	-2.649(0)	-5.094(0)	-4.968(0)
lnET2	-0.063(0)	-2.368(0)	-5.769(0)	-5.652(0)

Notes: 1. All the variables are measured in natural logarithms. 2. * and ** denote the rejection of the null hypothesis at the 5 percent and 10 percent level, respectively. 3. The numbers in parentheses indicate the order of augmentation selected on the basis of the Schwarz criterion.

Table 2. Estimation results using the OLS and the ECM

OLS (Dependent variable: lnGini)		ECM (Dependent variable: ΔlnGini)		
	Coefficient (std error)		Coefficient (std error)	Long-run elasticity
		$\Delta lnGrowth_t$	0.299 (0.140)**	
		$\Delta lnTFPall_t$	-0.167 (0.140)	
$lnGrowth_{t-1}$	0.091 (0.047)***	$lnGrowth_{t-1}$	0.086 (0.062)	0.156
$lnTFPall_{t-1}$	-0.111 (0.069)*	$lnTFPall_{t-1}$	-0.122 (0.068)*	-0.222
$lnTO_{t-1}$	0.164 (0.045)***	$lnTO_{t-1}$	0.075 (0.044)*	0.136
$lnFDI_{t-1}$	0.004 (0.011)	$lnFDI_{t-1}$	0.012 (0.007)*	0.022
$lnHDI_{t-1}$	-1.378 (0.316)***	$lnHDI_{t-2}$	-0.860 (0.470)*	1.563
		$lnGini_{t-1}$	-0.550 (0.156)***	
Constant	-2.282 (0.648)***	Constant	-1.695 (0.963)*	
Observations	29	Observations	28	
F-statistics	32.24***	F-statistics	3.68***	
Adjusted R^2	0.85	Adjusted R^2	0.44	

Notes: 1. The level of statistical significance is denoted as: * = 10 percent, ** = 5 percent, and *** = 1 percent. 2. Long-run elasticities can be computed by dividing the estimated coefficients of the level terms by the positive value of the coefficient of the lagged dependent variable.

The ECM results in Table 2 indicate that most of the variables have a long-run impact on income inequality, as shown by the significance of the estimated coefficients in the level rather than the change terms. TFP is statistically significant at the 10 percent level and negatively influences the Gini index in the long run, whereas the negative short-term impact does not appear to be significant. The long-run elasticity calculated from the steady-state solution is -0.22. The significant and negative impact implies that technological progress, measured as TFP, reduces income inequality in Thailand. This supports the current efforts of the Thai Government to promote technology and innovation as new drivers of growth. However, the result is not consistent with the SBTC theory and previous studies in developed countries. The reason could be that, in the case of Thailand, locally owned technology is far less advanced than that in high-income countries and is mainly all-purpose technology rather than ICT oriented. Thus, over the past three decades, its benefits have been shared more broadly. It is possible that the technological advances, especially in robotics, automation, and ICT, that potentially cause SBTC happened only recently and cannot be observed through TFP yet. These advanced IT-based technologies are also likely captured in foreign technologies that come with FDI and trade.

The trade openness and FDI are statistically significant, with the expected positive signs. Their significant impacts can only be observed in the long run, as shown by the coefficients expressed in level terms. The short-run impacts, expressed in first differences, are not significant and are dropped. The significant and positive impacts imply that increases in trade openness and FDI widen the income gap. These two main ingredients of globalization tend to benefit high-skilled workers, thus worsening the income inequality.

Other variables influencing the persistently high level of income inequality in Thailand are economic growth, measured as income per capita, and human capital, measured as the human development index (HDI). The growth–inequality relation is negative, implying that growth causes greater inequality but its impact only lasts in the short term. On the other hand, human capital development helps to reduce income inequality in the long run. The error correction coefficient or the coefficient of the lagged dependent variable ($Gini_{t-1}$) is statistically significant, with the expected negative signs, implying that the equilibrium relationship will hold in the long run.

4.3 Results from the Provincial-Level Models: What the Spatial Models Report

From the provincial-level models covering a shorter period (2009-2017), the impact of technology on inequality is positively signed but statistically insignificant in both the spatial lag and the spatial error model (Table 3). This holds true regardless of how the technology factor is measured. To be consistent with the national model, only the results using the overall TFP (TFPall) are reported. The positive and insignificant impacts indicate that, in the later period, when the rapidly changing technology is more evident worldwide, the direction of the technology impact tends to conform to the SBTC, but its influence may not be significant enough to be detected statistically.

The major factors influencing income inequality turn out to be economic growth (income per capita) and economic transformation, measured as the agricultural GDP shares. The impact of income per capita is negatively signed, implying that, as the country develops, growth reduces inequality. Although this finding is different from that of the national-level model, which indicates a positive short-run relationship, it is possible that the growth-inequality relationship is consistent with the Kuznets hypothesis, raising inequality in the short run and then reducing it in later periods. The impact of economic transformation (ET1) is positive, implying that, as the agricultural GDP shares decline, the low-earning groups receive higher incomes and hence the Gini index falls. This finding is consistent with the previous findings of Jaumotte et al. (2013). Nonetheless, human capital, measured as the shares of the labor force with at least secondary education, is insignificant. Other educational variables are also tested, and all are insignificant. The insignificance of educational inequality is likely to occur because this variable is not measured properly due to data constraints. Note that trade and FDI are not included due to data limitations.

The spatial lag and spatial error parameters are also statistically significant, confirming the existence of a spatial pattern. The significance of the spatial lag parameter implies that the Gini index in one province is associated with the Gini index in neighboring provinces, given that the spatial relationship is as specified by the weight matrix. Therefore, the neighborhood influence is significant (at the 10 percent level). The spatial dependence is also related to the locational factors captured in the spatial error model. The significance of the spatial error parameter (at the 1 percent level) confirms the spatial heterogeneity across the spatial data. That is, an area with high inequality typically occurs in certain similar conditions, such as the same sort of land or soil that is important for agriculture, similar non-farm job opportunities, transportation, infrastructure, and culture. In sum, the results reveal that income inequality occurs in those provinces related to their location. Accordingly, when estimating the determinants of income inequality, these underlying locational factors should be taken into account.

Table 3. Estimation results using panel data regression (the dependent variable is lnGini)

	Spatial lag	Spatial error
Economic growth: lnGrowth	-0.082 (0.014)***	-0.066 (0.012)***
Technological change: lnTFPall	0.005 (0.070)	0.036 (0.022)
Human capital: lnEdu	-0.011 (0.038)	-0.015 (0.035)
Economic transformation: lnET1	0.021 (0.009)***	0.023 (0.008)***
Constant	-0.027 (0.084)	-0.034 (0.072)
Spatial lag parameter: ρ (p-value)	-0.19 (0.10)*	
Spatial error parameter: λ		-0.37 (0.00)***
Log likelihood	570.16	572.57
LM test of ρ: chi2(1)	2.96 (0.08)*	
LM test of λ: chi2(1)		10.69 (0.00)***
Observations	380	380

Notes: The standard errors of the estimated coefficients are in parentheses, except spatial parameters and LM tests, for which the p-value is reported in parentheses. *** and * mean significance at the 1 percent and the 10 percent level.

5. Conclusion

This study is the first attempt to examine the relationship between technological change and income inequality in Thailand. It applies regression analysis to both annual and provincial data. The overall results show that advances in technology (overall TFP growth) reduce income inequality in the long run, suggesting the important role of technological development policies. However, care should be given to the incoming new technology, especially technology that comes with FDI and trade, which is likely to favor high-skilled workers in the near future. Labor skill improvement and social welfare programs could help the low-skilled workers to reap more benefits from the change in technology.

Other factors that help in alleviating inequality are human capital, income per capita, and declining agricultural GDP shares. Therefore, government policies should continue to support human capital development (particularly education and health) and generate more non-farm job opportunities, especially in high-value-added activities such as services that will raise the incomes of the low-earning groups. In contrast, local measures (for example, tax incentives and investment promotion measures) should be reinforced to ensure the benefits from trade and FDI are shared more broadly. Social protection of low-skilled workers should also be strengthened. Additionally, the significance of spatial correlation among provinces implies that the policy should target groups of provinces in close proximity or larger regional bases rather than focusing on various small areas.

Further studies could improve the measurement of several variables used in this study. For example, TFP could be measured using other methods and the ICT capital stock should be examined as in many previous studies. Income inequality could be measured using other measures such as Gini based on expenditure and income gap. Other aspects of inequality, such as asset, shall also be explored. Educational inequality should also be measured more appropriately, for example by calculating the Gini coefficient for education. Trade and FDI should be included in the provincial-level model. However, whether it is possible to improve these limitations is subject mainly to the data availability. If the data constraints can be overcome, the empirical findings should yield more fruitful recommendations.

References

Abramovitz, M. (1956). Resource and output trends in the United States since 1870. *American Economic Review*, *46*(2), 5-23.

Acemoglu, D. (2002). Technical change, inequality and the labor market. *Journal of Economic Literature*, *40*(1), 7-72.

Acemoglu, D. (2003). *Technology and inequality* (NBER Report). Retrieved from https://www.nber.org/reporter/winter03/technologyandinequality.html

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Boston: Kluwer Academic.

Anselin, L. (1999). *Spatial econometrics*. Bruton: Center School of Social Sciences, University of Texas at Dallas.

Athukorala, P., & Sen, K. (2002). Appendix 2: The econometric methodology. In P. Athukorala & K. Sen (Eds.), *Saving, investment and growth in India*. Oxford: Oxford University Press.

Behar, A. (2016). The endogenous skill bias of technical change and wage inequality in developing countries. *Journal of International Trade & Economic Development*, *25*(8), 1101-1121.

Chen, E. K. Y. (1997). The total factor productivity debate: Determinants of economic growth in East Asia. *Asian-Pacific Economic Literature*, *11*(1), 18-38.

Deskoska, E., & Vlčková, J. (2018). The role of technological change in income inequality in the United States. *Acta Oeconomica Pragensia*, *2018*(1), 47-66.

Ding, S., Meriluoto, L., Reed, W. R., Tao, D., & Wu, H. (2011). The impact of agricultural technology adoption on income inequality in rural China: Evidence from southern Yunnan Province. *China Economic Review*, *22*(3), 344-356.

Griliches, Z. (1996). The discovery of the residual: A historical note. *Journal of Economic Literature*, *34*(3), 1324-1330.

Hendry, D. F. (1995). *Dynamic econometrics*. Oxford: Oxford University Press.

Inder, B. (1993). Estimating long-run relationships in economics: A comparison of different approaches. *Journal of Econometrics*, *57*(1-3), 53-68.

International Monetary Fund (IMF). (2016). *Sharing the growth dividend: Analysis of inequality in Asia*. Washington, DC: Regional Economic Outlook. Asia Pacific. Building on Asia's strengths during turbulent times.

Jaumotte, F., Lall, S., & Papageorgiou, C. (2013). Rising income inequality: Technology, or trade and financial globalization? *IMF Economic Review*, *61*(2), 271-309.

Jin, F., & Lee, K. (2017). Dynamics of the growth-inequality nexus in China: Roles of surplus labor, openness, education, and technical change in province-panel analysis. *Journal of Economic Policy Reform*, *20*(1), 1-25.

Jitsuchon, S. (2014). Income inequality, poverty and labor migration in Thailand. *Singapore Economic Review*, *59*(1), 1-16.

Jitsuchon, S. (2015). *Inequality in Thailand: Trends, policies, and policy implementation* (Research report). Bangkok: Thailand Development Research Institute. (in Thai)

Kristal, T., & Cohen, Y. (2017). The causes of rising wage inequality: The race between institutions and technology. *Socio-Economic Review*, *15*(1), 187-212.

Krongkaew, M. (1985). Agricultural development, rural poverty, and income distribution in Thailand. *Developing Economies*, *23*(4), 325-346.

Kuznets, S. (1955). Economic growth and income inequality. *American Economic Review*, *45*(1), 1-28.

National Economic and Social Development Board (NESDB). (2018). *Analysis of poverty and inequality situation in Thailand*. Bangkok: NESDB. (in Thai)

OECD. (2011). *An overview of growing income inequalities in OECD countries: Main findings*. Retrieved from https://www.oecd.org/els/soc/49499779.pdf

Paweenawat, S. W., & McNown, R. (2014). The determinants of income inequality in Thailand: A synthetic cohort analysis. *Journal of Asian Economics*, *31-32*(2014), 10-21.

Perkins, D., Radelet, S., Lindauer, D., & Block, S. (2013). Chapter 6. In *Inequality and poverty. Economics of development* (7th edition). New York: W. W. Norton & Company.

Pootrakul, K. (2013). Quality of growth from the perspective of income distribution: Problems and solutions. In *BOT Symposium 2013: Lifting Barriers to Sustainable Growth*. Bangkok: Centara Grand at Central World.

Preechametta, A. (2015). Dynamics of income inequality under social identity hypothesis. *Applied Economics Journal*, *22*(2), 1-24. (in Thai)

Rodríguez-Pose, A., & Tselios, V. (2009). Education and income inequality in the regions of the European Union. *Journal of Regional Science*, *49*(3), 411-437.

Salverda, W., Nolan, B., & Smeeding, T. (2011). Introduction. In B. Nolan, W. Salverda, & T. Smeeding (Eds.), *The Oxford handbook of economic inequality* (pp.1-21). Oxford: Oxford University Press.

Santos, M., Sequeira, T. N., & Ferreira-Lopes, A. (2017). Income inequality and technological adoption. *Journal of Economic Issues*, *51*(4), 979-1000.

Schultz, T. W. (1953). *The economic organization of agriculture*. New York: McGraw-Hill.

Sequeira, T. N., Santos, M., & Ferreira-Lopes, A. (2017). Income inequality, TFP, and human capital. *Economic Record*, *93*(300), 89-111.

Solow, R. M. (1957). Technical change and aggregate production function. *Review of Economics and Statistics*, *39*(3), 312-320.

Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics*, *87*(3), 355-374.

Suphannachart, W., & Warr, P. (2012). Total factor productivity in Thai agriculture: Measurement and determinants. In K. O. Fuglie, S. L. Wang, & V. E. Ball (Eds.), *Productivity growth in agriculture: An international perspective*. Oxfordshire: CAB International.

Warr, P. (2014). Agricultural liberalization, poverty and inequality: Indonesia and Thailand. *Journal of Asian Economics*, *35*(2014), 92-106.

World Bank. (2002). *Achieving education for all by 2015: Simulation results for 47 low-income countries*. Washington, DC: World Bank.

Xu, Y., & Ouyang, A. Y. (2015). China wage inequality: The role of trade and technology. *Journal of Applied Economics*, *47*(47), 5057-5071.