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Analysis of Changes in Thailand's Income Distribution from 2013 to 2021 using Growth Incidence and Delta Lorenz Curves

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Abstract

The objective of this study is to analyze changes in income distribution of Thailand between 2013 and 2019 and between 2019 and 2021. Using the growth incidence curve analysis and the delta Lorenz curve analysis developed by Ferreira et. al. (2019), not only we can analyze changes in income distribution thru its summary statistics, but we can also analyze the income level growth and income share of Thai households in every quantile of the distribution. We found that the improvements in Thailand's inequality are different in these two time periods. The counterfactual analysis confirmed that Thailand's inequality should be better than they actually are.

Keywords: Growth Incidence Curve, Delta Lawrence Curve, Inequality

JEL Classification Code: C14, O15

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1. Introduction

Thailand, a vibrant Southeast Asian nation, has experienced significant economic growth over the decades in the past. As the country progresses, understanding the dynamics of income distribution becomes crucial for ensuring equitable development and addressing social disparities. Income distribution is a fundamental aspect of economic welfare (Tinbergen (1957), Kakwani (1980)) and plays a pivotal role in shaping social cohesion and stability (Phongpaichit and Baker (2015)).

The main objective of this study is to analyze the shifts in Thailand's income distribution from 2013 to 2021. To achieve this goal, we employ two key analytical tools: Growth Incidence Curves (GIC) and Delta Lorenz Curves (DLC) (Ferreira, Firpo, and Galvao (2019)). GIC allows us to examine the annualized growth rates of income across different population groups, shedding light on how economic progress is distributed among different segments of society. DLC, on the other hand, provide insights into the cumulative change in income share up to each quantile $\alpha \in (0,1)$ of the distribution. We also want to explore the redistributive impact from the social assistance program.

Previous research on income distribution in Thailand has shed light on various dimensions of this issue. Studies have examined the impact of economic policies, demographic factors, and social programs on income inequality (Limwattananon et. al. (2011), Paweenawat and McNown (2014), Thepsumroeng (2019), Jaitiang, Huang, and Yang (2021), Karim (2021), Somjai (2021), Puttanapong, Luenam, and Jongwattanakul (2022), Sangkasem and Puttanapong (2022), and Sitthiyot and Holasut (2023)).

Chotikapanich (1993) compares different functional forms for the Lorenz curve, which is a graphical representation used to depict income distribution and inequality. The author aims to examine the characteristics and properties of various functional forms and assess their suitability in representing income inequality. The article discusses several alternative functional forms for the Lorenz curve, including the beta, gamma, and Singh-Maddala forms. The author compares these forms based on their ability to capture different shapes of income distribution and their goodness-of-fit to empirical data. The findings of the study provide insights into the strengths and limitations of different functional forms for the Lorenz curve.

Kakwani (2000) provides a comprehensive analysis of poverty dynamics by examining the contributions of economic growth and income inequality to changes in poverty over time. The study introduces the concept of the growth-inequality-poverty (GIP) triangle, which combines measures of economic growth, income inequality, and poverty to analyze their interrelationships. The author proposes a method to decompose changes in poverty into growth and inequality components and applies this framework to empirical data from Thailand. The findings of the study reveal the contributions of economic growth and income inequality to changes in poverty levels in Thailand. The study also highlights the potential policy implications for poverty reduction strategies, emphasizing the need for inclusive and equitable growth.

Deolalikar (2003) also focuses on examining the relationship between poverty, economic growth, and income inequality in Thailand. The author aims to provide a comprehensive analysis of these interrelated factors and their implications for poverty reduction strategies. The author then presents empirical evidence and statistical analysis to assess the trends in poverty, growth, and inequality in Thailand over a specific period. The analysis demonstrates that while Thailand has experienced significant economic growth, poverty reduction has not been uniform, and income inequality has persisted.

Son (2004) focuses on the concept of pro-poor growth, which refers to economic growth that disproportionately benefits the poor and reduces income inequality. The author presents a brief analysis and discussion of the characteristics and measurement of pro-poor growth. The article explores the existing literature on pro-poor growth and offers insights into the methods and indicators used to assess its occurrence. The author highlights the importance of considering both the growth rate of average income and the distributional changes in income when evaluating the pro-poor nature of economic growth. The findings of the study provide insights into the complexities and challenges associated with measuring pro-poor growth. The author discusses various measurement approaches and emphasizes the need for context-specific analyses that consider the specific circumstances of each country or region.

Kurita and Kurosaki (2011) examine the dynamics of economic growth, poverty, and inequality in Thailand using panel data at the regional level. The authors investigate the factors that contribute to these dynamics, including regional characteristics, government policies, and demographic factors. The findings of the study reveal the complex dynamics between growth, poverty, and inequality in Thailand. The analysis highlights regional disparities within and examines the factors that drive these variations.

Paweenawat and McNown (2014) focuses on examining the determinants of income inequality in Thailand using a synthetic cohort analysis. The authors aim to identify the factors that contribute to income inequality and assess their impact over time. The article utilizes data from the Thailand Socioeconomic Survey to construct synthetic cohorts, which allow for the analysis of income inequality across different birth cohorts. The authors employ various statistical techniques to explore the relationship between income inequality and a range of factors, including education, occupation, sector of employment, and demographic characteristics. The findings of the study highlight the significant role of education in shaping income disparities, with higher levels of education associated with lower income inequality. The findings can inform policymakers and stakeholders in designing targeted strategies to address income inequality, particularly by focusing on improving educational opportunities and reducing skill gaps among different segments of the population.

Vanitcharearnthum (2019) focuses on examining top income shares and their impact on inequality in Thailand. The author aims to provide empirical evidence and analysis of the distribution of income among the top earners and its implications for overall income inequality. The article utilizes data from various sources, including income tax records and household surveys, to analyze the concentration of income among the top earners in Thailand. The author employs statistical methods to estimate and compare the top income shares over time and assess their relationship with overall income inequality. The findings highlight the growing concentration of income among the highest income earners and its contribution to overall inequality in the country.

Thepsumroeng (2019) provides valuable insights into the trends and dynamics of income inequality in Thailand over the period from 2009 to 2017 using the Gini coefficient as a measure of inequality. The article utilizes household-level data and employs the Gini coefficient to quantify income inequality in Thailand. The findings of the study reveal the income distribution dynamics in Thailand during the studied period. The analysis of the Gini coefficient demonstrates the changes in income inequality and allows for comparisons between different years.

Yang, Wang, and Dewina, (2020) assess the current status of poverty and inequality in Thailand by examining various indicators and trends. They utilize data from national surveys and employ statistical techniques to measure and analyze poverty and inequality levels. The article presents key findings related to poverty and inequality in Thailand, including the poverty rate, income distribution, and inequality measures such as the Gini coefficient. The authors discuss the factors that contribute to these patterns and highlight the implications for social and economic development in the country. The analysis reveals that while Thailand has made progress in poverty reduction, income inequality remains a challenge. The article discusses the drivers of inequality, such as disparities in education, access to resources, and geographic location. The authors also explore the policy implications of these findings, suggesting potential strategies for addressing poverty and inequality in Thailand.

Sitthiyot and Holasut (2021) develop a method for estimating the Lorenz curve, a graphical representation used to depict income distribution and inequality. The article introduces the methodology, which involves utilizing cumulative distribution functions (CDF) and kernel density estimation to estimate the Lorenz curve. The findings of the study demonstrate the effectiveness of the proposed approach in estimating the Lorenz curve, highlighting its simplicity and accuracy. The authors provide empirical illustrations and comparisons with existing methods to showcase the practicality and validity of their proposed methodology.

However, there remains a gap in the literature regarding the specific analysis of income distribution changes using GIC and DLC in Thailand. By utilizing these tools, we aim to fill this gap and provide a comprehensive understanding of income distribution dynamics in the country.

Many studies have focused on specific time periods or cross-sectional analyses, leaving gaps in understanding the long-term dynamics of income inequality in Thailand. Research that spans multiple years and captures changes over time is necessary to identify trends, patterns, and the underlying drivers of income inequality.

Assessing the effectiveness of existing policies and interventions aimed at reducing income inequality in Thailand is an important research gap. Evaluating the impact of specific policies, such as social protection programs, labor market reforms, and tax policies, can provide insights into their effectiveness and inform evidence-based policy recommendations.

This study endeavors to contribute to the existing body of knowledge on income distribution in Thailand. By employing GIC and DLC, we offer a comprehensive analysis of income distribution changes, providing valuable insights into the pro-poor or pro-rich nature of economic growth in Thailand. These findings can inform policymakers in their efforts to design and implement policies that promote inclusive growth and reduce income disparities.

2. Model and Methodology

Consider an income (random) variable Y at two different time periods t = 0 and t = 1. The cumulative distribution functions (CDF) of this random variable in these two time periods are denoted by F_{Y0} and F_{Y1} respectively. Many economists studied the changes in income distribution via the summary statistics of these income distributions such as the growth rate of the mean income,

$$\gamma = \frac{\mu_1}{\mu_0} - 1, \quad (1)$$

where $\mu_t = \int_{-\infty}^{+\infty} y dF_{Yt}(y)$ is the mean income level at period t.

Another approach to study the changes in income distribution is to construct some measures from the distribution. Define the quantile function q to be the (left) inverse of the CDF, that is define $q_0(\alpha) = F_{Y0}^{-1}(\alpha)$ and $q_1(\alpha) = F_{Y1}^{-1}(\alpha)$ for all $\alpha \in (0,1)$. The quantile function is used to construct a well-known Lorenz curve defined by

$$L_t(\alpha) = \int_0^\alpha \frac{q_t(a)}{\mu_t} da. \quad (2)$$

The Lorenz curve is frequently used to study the income inequality problem in the economy. One popular statistic derived from the Lorenz curve is the Gini coefficient,

$$G_t = 1 - 2\int_0^1 L_t(\alpha)\, d\alpha. \quad (3)$$

The change in income inequality can be measured by the change in Gini coefficients $\Delta_G = G_1 - G_0$. A limitation of the analysis of the change of income distribution from the growth rate of the mean income or the change in Gini coefficients is that they are just summary statistics of the distributions, they did not give the picture of the evolution of the whole income distributions. Instead of looking at the growth rate of the mean income, Ravallion and Chen (2003) introduced the growth incidence curve (GIC), which is the curve representing the income growth rate at each given quantile α,

$$GIC(\alpha) = \frac{q_1(\alpha)}{q_0(\alpha)} - 1, \quad (4)$$

provided that $q_0(\alpha) \neq 0$. The GIC can be used for the income inequality comparison but not for the study of individual movement over time because any individual could be at different quantile at different time. Ferreira et. al. (2019) showed that the growth rate of the mean income γ is the weighted average of the GIC across quantiles which is in general different from the simple average of the GIC across quantiles, $\bar{\gamma} = \int_0^1 GIC(\alpha)d\alpha$.

With the same reason, instead of looking at the change in Gini coefficients, economists should look at the change in the whole Lorenz curve. The difference of the Lorenz curves between two periods is called the delta Lorenz curve (DLC), which is defined by,

$$DLC(\alpha) = \Delta_L(\alpha) = L_1(\alpha) - L_0(\alpha). \qquad (5)$$

The DLC is a mean independent analog of the GIC. The main difference between GIC and DLC is that GIC gives the quantile-specific growth rate of the income *level,* but DLC gives the changes over time in the income *share* cumulatively appropriated by all quantiles up to α.

2.1 Analysis of the change in income distribution

There are many reasons why the income distribution changes over time. The change could be caused by a change in some covariate affecting the income of the population or it could be caused by the change in the structure of the economy or some economic shock. To analyze the change in income distribution, we need to decompose the change in income distribution into those two parts. To be able to do that, we need to construct a counterfactual income distribution F_{Y1}^*, which is the income distribution given that the joint distribution of all *d* observable covariates $X = (X_1, \dots, X_d)$ does not change. Hence, the change in income distribution can be decomposed as

$$F_{Y1}(y) - F_{Y0}(y) = \left(F_{Y1}(y) - F_{Y1}^*(y)\right) + \left(F_{Y1}^*(y) - F_{Y0}(y)\right). \qquad (6)$$

The first term $F_{Y1}(y) - F_{Y1}^*(y)$ represents the change in income distribution caused by a change in joint distribution of the observable covariates and it is called the composition effect. The second term $F_{Y1}^*(y) - F_{Y0}(y)$, which is called the structure effect, represents the change in income distribution caused by a change in unobservable covariates or a structural change or both.

Let F_{X0} denote the joint distribution of all *d* observable covariates at period t = 0, the counterfactual income distribution F_{Y1}^* is defined by

$$F_{Y1}^{*}(y) = \int F_{Y|X1}(y|x)dF_{X0}(x), \tag{7}$$

Where $F_{Y|X1}$ is the conditional distribution of Y given X at period t = 1 and the region of integration is over the support of the joint distribution of all d observable covariates. Whence the counterfactual income distribution is defined, the counterfactual quantile is defined as the (left) inverse of the counterfactual distribution, i.e., $q_1^*(\alpha) = F_{Y1}^{*-1}(\alpha)$ for all $\alpha \in (0,1)$.

Similarly, we can do the counterfactual analysis of the change in income distribution by using the counterfactual distribution instead of the actual distribution. The counterfactual GIC, which is the growth incidence curve if the distribution of the covariates does not change, can be defined as

$$GIC^*(\alpha) = \frac{q_1^*(\alpha)}{q_0(\alpha)} - 1 \tag{8}$$

and the counterfactual DLC is now defined as

$$DLC^*(\alpha) = \Delta_L^*(\alpha) = L_1^*(\alpha) - L_0(\alpha), \tag{9}$$

where $L_1^*(\alpha) = \int_0^{\alpha} \frac{q_1^*(a)}{\mu_1^*} da$ is the counterfactual Lorenz curve and $\mu_1^* = \int_{-\infty}^{+\infty} y dF_{Y1}^*(y)$ is the counterfactual mean income.

Given the counterfactual GIC and counterfactual DLC, the counterfactual analog of the interested parameters can also be calculated. For example, the counterfactual mean income growth rate is $\gamma^* = \frac{\mu_1^*}{\mu_0} - 1$, the counterfactual average income growth is $\bar{\gamma}^* = \int_0^1 GIC^*(\alpha)d\alpha$, and the counterfactual change in Gini coefficients is $\Delta_G^* = G_1^* - G_0$, where $G_t^* = 1 - 2\int_0^1 L_t^*(\alpha)d\alpha$ is the counterfactual Gini coefficient of period t.

2.2 Estimation and Inference

Ferreira et. al. (2019) showed that all the quantile functions, both actual and counterfactual ones, can be estimated by using the weighted quantile regressions framework introduced by Koenker and Bassett (1978).

Let $p(X)$ be the conditional probability of being observed at period 1 given X and p be its unconditional probability. The conditional probability is estimated by using the logit model to obtain the estimator $\hat{p}(X)$ and the unconditional probability is estimated by the sample average, $\hat{p} = \bar{T}$, where T = 0 or 1 is a dummy variable.

The quantile functions are estimated by using the weighted quantile regressions, where $\widehat{w}_{1i} = T_i/\hat{p}$, $\widehat{w}_0 = (1 - T_i)/(1 - \hat{p})$, and $\widehat{w}_1^* = \left(\frac{1-\hat{p}(X_i)}{\hat{p}(X_i)}\right)\left(\frac{T_i}{1-\hat{p}}\right)$ are the weights of each observation $i = 1, \dots, n$ for the quantile estimators $\hat{q}_1(\alpha)$, $\hat{q}_0(\alpha)$, and $\hat{q}_1^*(\alpha)$, respectively.

Once the quantile functions are estimated, the actual and counterfactual GIC can be simply estimated by

$$\widehat{GIC}(\alpha) = \frac{\hat{q}_1(\alpha)}{\hat{q}_0(\alpha)} - 1, \tag{10}$$

$$\widehat{GIC}^*(\alpha) = \frac{\hat{q}_1^*(\alpha)}{\hat{q}_0(\alpha)} - 1. \tag{11}$$

The actual and counterfactual Lorenz curves, the actual and counterfactual DLC, and other parameters of interest can be estimated by using the estimated quantile functions straightforwardly.

Ferreira et. al. (2019) proved that, under some assumptions, these quantile function estimators are uniformly consistent and have asymptotic mean zero Gaussian process. Thus the asymptotic distribution of the actual and counterfactual GIC estimators can be derived using the delta method.

Let $\beta(\alpha)$ be a functional of the actual and counterfactual quantile functions and $r(\alpha)$ be a known bounded continuous function of α. Consider testing a null hypothesis,

$$H_0: \beta(\alpha) - r(\alpha) = 0 \text{ uniformly for all } \alpha. \tag{12}$$

There are many ways to test this null hypothesis. Let $\hat{\beta}(\alpha)$ be the estimate of $\beta(\alpha)$, then one can construct the Kolmogorov-Smirnov type test statistic,

$$KS = \sqrt{n} \sup_{\alpha} \left|\hat{\beta}(\alpha) - r(\alpha)\right|, \tag{13}$$

or the Cramér-von Mises type test statistic,

$$CvM = \sqrt{n} \int_0^1 \left|\hat{\beta}(\alpha) - r(\alpha)\right| d\alpha. \tag{14}$$

If the function $r(\alpha)$ is unknown but can be estimated consistently and uniformly over α by $\hat{r}(\alpha)$, then the Kolmogorov-Smirnov and Cramér-von Mises type test statistics can be modified by replacing the function $r(\boldsymbol{\alpha})$ by its estimate $\hat{r}(\alpha)$. The critical values of these tests can be obtained by using the recentered bootstrap procedure.

3. Data and Results

3.1 Data

The data for this study are from the annual Household Socio-Economic Survey (SES) for the years 2013–2021 collected by the National Statistical Office (NSO) of Thailand in all the 77 provinces of Thailand. The data are repeated cross-sections in which households are randomly selected in each round of the surveys. The NSO collects detailed household data for SES on income, expenditure and consumption of commodities, assets and liabilities, durable goods ownership, social assistance programs, and information on members and heads of the households.

The study period covers a period of seven years before the COVID-19 (2013–2019) and three years during the pandemic (2019–2021). The unit of analysis of wealth distribution at the household level. The variable of interest for the distribution analysis is the real per capita monthly income of each household (*Income*) in 2020 Baht. The observable covariates compose of age of the household head (*Age*) and its squared, years of schooling of the household head (*Schooling*) and its squared, rural dummy (*Rural*=1 represents rural area), gender dummy (*Female* = 1 if household head is female), marital status dummy (*Married* =1 if household head is married), and agricultural sector dummy (*Agriculture*=1 if primary or secondary occupation of household head is in agricultural sector). Regional dummies are also included in the logit regression analysis. Household with missing values in any of these variables are omitted from the sample. The top and bottom 0.5% of the income variable are trimmed off to reduce outliers.

3.2 GIC and DLC of Thailand (2013 – 2019)

The summary statistics of the income variable and the observable covariates of Thailand in 2013 and 2019 are presented in Table 1.

Year	2013 (n = 42307)						2019 (n = 45126)					
Variable	Mean	Min	Q1	Median	Q3	Max	Mean	Min	Q1	Median	Q3	Max
Income	9500	736.8	4028.3	6620	11464.9	72919.5	9766	1069	4406	7013	11813	68232
Age	52.38	10	42	52	63	98	55.44	11	45	56	66	98
Schooling	7.162	0	4	6	12	22	7.329	0	4	6	12	22
Rural	0.3873	0	0	0	1	1	0.4334	0	0	0	1	1
Married	0.6557	0	0	1	1	1	0.6241	0	0	1	1	1
Female	0.3742	0	0	0	1	1	0.4048	0	0	0	1	1
Agriculture	0.3264	0	0	0	1	1	0.2991	0	0	0	1	1

Table 1 Summary statistics of the income variable and the observable covariates of Thailand in 2013 and 2019

From Table 1 we can see that the mean per capita (real) income of the household increased from 9500 Baht in 2013 to 9766 Baht in 2019. Thus, the growth rate of mean income (γ) between 2013 and 2019 is 0.028 or 2.8%. The Gini coefficient decreases from 0.406 in 2013 to 0.385 in 2019, a decrease of 0.021. The growth incidence curve ($\widehat{GIC}$) and its counterfactual ($\widehat{GIC}^*$) are shown in Figure 1.

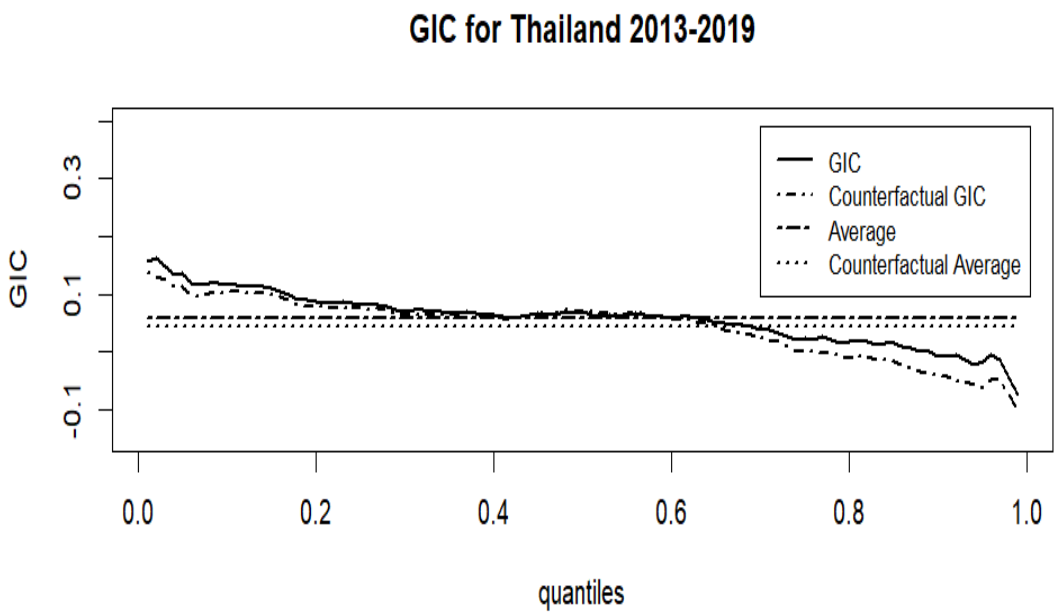

Figure 1 Growth incidence curve and its counterfactual for Thailand 2013–2019

From Figure 1, the growth incidence decreases from 0.16 to -0.07. The households below the 90th percentile have positive income growth, but the top ten percent of the households have negative income growth. The average income growth rate ($\bar{\gamma}$) is about 0.059

or 5.9%. The counterfactual growth incidence decreases from 0.136 to -0.101. The counterfactual GIC showed that the households below the third quartile would have positive income growth and the top 25% of the households would have negative income growth. The counterfactual average income growth rate ($\bar{\gamma}^*$) is about 0.045 or 4.5%. Moreover, the GIC is uniformly above its counterfactual. The results of KS tests and CvM tests of GIC and its counterfactual are shown in Table 2.

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$GIC(\alpha) = 0$	47.9	14.4	15.9	18.2	18.38	3.70	4.32	5.34
$GIC(\alpha) = \bar{\gamma}$	39.6	13.5	15.2	17.9	9.67	2.62	2.82	3.44
$GIC^*(\alpha) = 0$	40.2	13.7	15.4	17.7	17.71	3.22	3.64	4.37
$GIC^*(\alpha) = \bar{\gamma}^*$	43.2	13.4	15.2	17.7	12.33	2.52	2.76	3.28

Table 2 The hypothesis testing results of GIC and its counterfactual of Thailand 2013–2019

From Table 2 we can see that both KS tests and CvM tests give the same conclusions. Both tests reject the null hypothesis that there is no income growth in all quantiles at 0.01 significance level. Also both tests reject the null hypothesis that the income growth of all quantiles is equal to its average growth rate at 0.01 significance level. Conditional on observable covariates, both tests reject the null hypothesis that there is no income growth in all quantiles at 0.01 significance level and they reject the null hypothesis that the income growth of all quantiles is equal to its average growth rate at 0.01 significance level as well. The delta Lorenz curves (Δ_L) and its counterfactual (Δ_L^*) are presented in Figure 2.

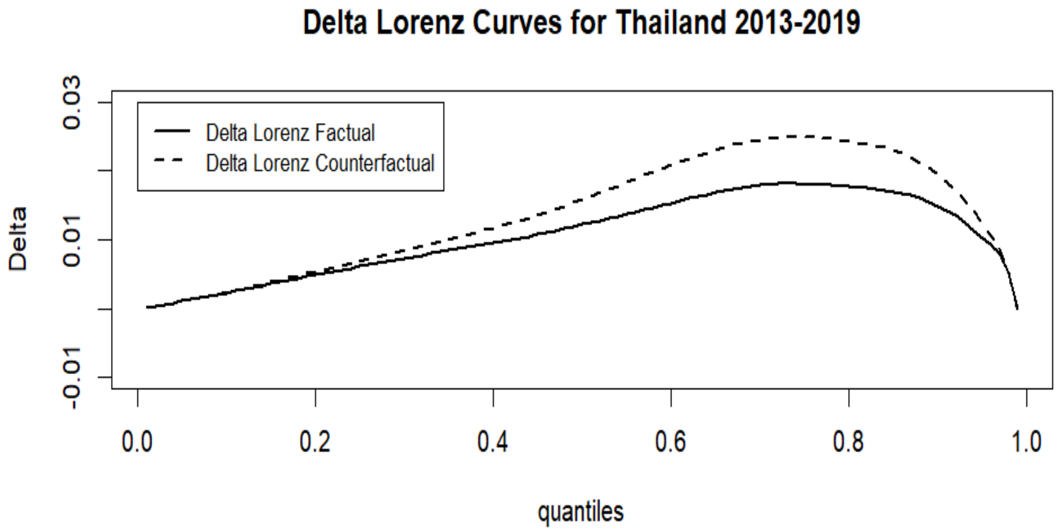

Figure 2 Delta Lorenz Curves and its counterfactual for Thailand 2013 – 2019

From Figure 2, the DLC is positive at all quantiles and it reaches its maximum of 0.0181 at the 73rd percentile. The counterfactual DLC is also positive at all quantiles and it reaches its maximum of 0.025 at the 73rd percentile as well. Moreover, the counterfactual DLC is uniformly above the factual DLC. The results of KS tests and CvM tests of DLC and its counterfactual are shown in Table 3.

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$\Delta_L(\alpha) = 0$	5.36	1.46	1.75	2.09	3.093	0.673	0.796	1.002
$\Delta_L^*(\alpha) = 0$	7.39	1.47	1.71	2.17	4.005	0.624	0.752	1.029

Table 3 The hypothesis testing results of DLC and its counterfactual of Thailand 2013–2019

From Table 3 we can see that both KS tests and CvM tests give the same conclusions. Both tests reject the null hypothesis that the inequality is constant at 0.01 significance level. Conditional on observable covariates, both tests reject the null hypothesis that the inequality is constant at 0.01 significance level as well.

3.3 GIC and DLC of Thailand (2019 – 2021)

The summary statistics of the income variable and the observable covariates of Thailand in 2019 and 2021 are presented in Table 4.

Year	2019 (n = 45126)						2021 (n = 46370)					
Variable	Mean	Min	Q1	Median	Q3	Max	Mean	Min	Q1	Median	Q3	Max
Income	9766	1069	4406	7013	11813	68232	10113	1241	4603	7207	12058	70533
Age	55.44	11	45	56	66	98	56.21	13	46	57	66	98
Schooling	7.329	0	4	6	12	22	7.596	0	4	6	12	21
Rural	0.4334	0	0	0	1	1	0.4342	0	0	0	1	1
Married	0.6241	0	0	1	1	1	0.6119	0	0	1	1	1
Female	0.4048	0	0	0	1	1	0.4265	0	0	0	1	1
Agriculture	0.2991	0	0	0	1	1	0.3134	0	0	0	1	1

Table 4 Summary statistics of the income variable and the observable covariates of Thailand in 2019 and 2021

From Table 4 we can see that the mean per capita (real) income of the household increased from 9766 Baht in 2019 to 10113 Baht in 2021. Thus, the growth rate of mean income (γ) between 2019 and 2021 is 0.0355 or 3.55%. The Gini coefficient decreases from 0.385 in 2019 to 0.384 in 2019, a decrease of only 0.001. The growth incidence curve ($\widehat{GIC}$) and its counterfactual ($\widehat{GIC}^*$) are shown in Figure 3.

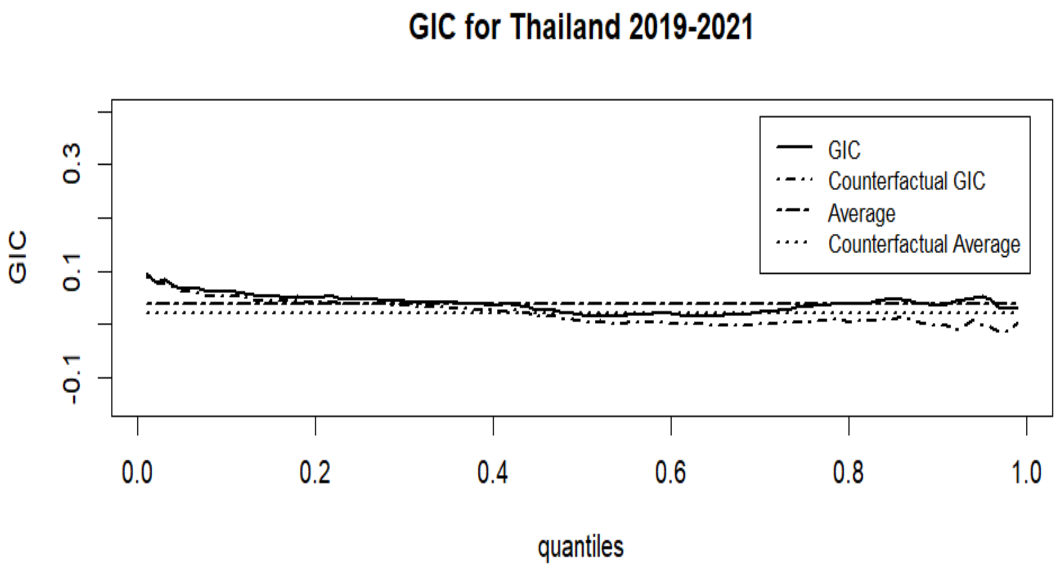

Figure 3 Growth incidence curve and its counterfactual for Thailand 2019–2021

From Figure 3, the growth incidence is quite flat around its average ($\bar{\gamma}$) which is about 0.039 or 3.9%. The counterfactual growth incidence is also fluctuated around its average ($\bar{\gamma}^*$) of 0.021 or 2.1%. Moreover, the GIC is uniformly above its counterfactual. The results of KS tests and CvM tests of GIC and its counterfactual are shown in Table 5.

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$GIC(\alpha) = 0$	28.7	14.5	16.2	19.9	11.81	3.60	4.07	4.78
$GIC(\alpha) = \bar{\gamma}$	27.2	13.4	14.6	17.3	6.72	2.87	3.15	3.78
$GIC^*(\alpha) = 0$	16.7	13.9	15.5	19.3	3.89	2.42	2.76	3.35
$GIC^*(\alpha) = \bar{\gamma}^*$	20.8	12.8	14.2	17.3	5.85	2.26	2.47	2.95

Table 5 The hypothesis testing results of GIC and its counterfactual of Thailand 2019–2021

From Table 5 we can see that both KS tests and CvM tests reject the null hypothesis that there is no income growth in all quantiles at 0.01 significance level. Also both tests reject the null hypothesis that the income growth of all quantiles is equal to its average growth rate at 0.01 significance level. Conditional on observable covariates, CvM test rejects the null hypothesis that there is no income growth in all quantiles at 0.01 significance level but KS test rejects this null hypothesis at 0.05 significance level. Both tests reject the null hypothesis that, conditional on observable covariates, the income growth of all quantiles is equal to its average growth rate at 0.01 significance level as well. The delta Lorenz curves (Δ_L) and its counterfactual (Δ_L^*) are presented in Figure 4.

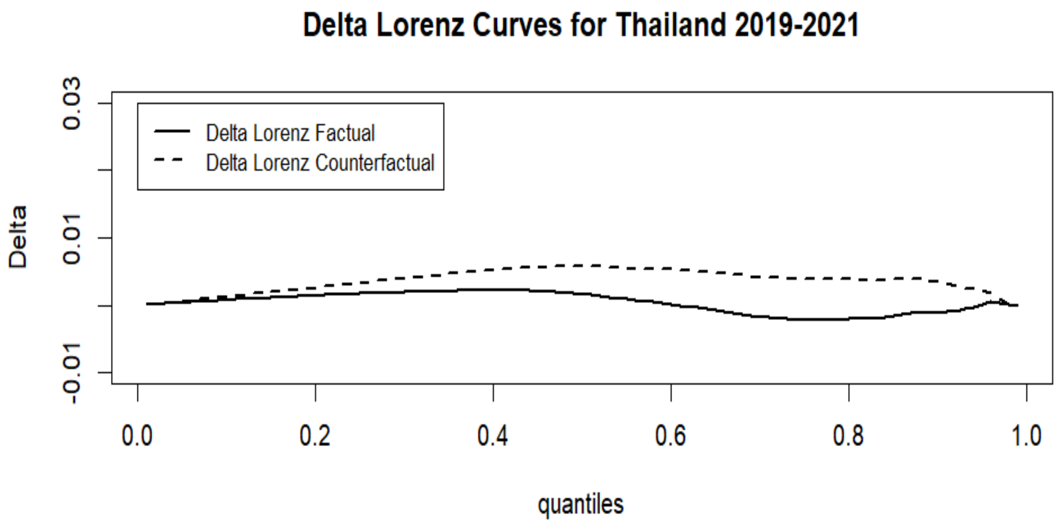

Figure 4 Delta Lorenz Curves and its counterfactual for Thailand 2019 – 2021

From Figure 4, the DLC fluctuates around zero. It is positive at the beginning until the 60th percentile it turns negative. The DLC has positive value again after the 95th percentile. On the contrary, The counterfactual DLC is positive at all quantiles. The counterfactual keeps increasing until it pass its median and then it decreases. Moreover, the counterfactual DLC is uniformly above the factual DLC. The results of KS tests and CvM tests of DLC and its counterfactual are shown in Table 6.

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$\Delta_L(\alpha) = 0$	0.676	1.381	1.615	2.017	0.398	0.634	0.746	0.934
$\Delta_L^*(\alpha) = 0$	1.75	1.28	1.44	1.90	1.098	0.566	0.661	0.917

Table 6 The hypothesis testing results of DLC and its counterfactual of Thailand 2019–2021

From Table 6 we can see that both KS tests and CvM tests do not reject the null hypothesis that the inequality is constant at 0.1 significance level. Conditional on observable covariates, CvM test rejects the null hypothesis that the inequality is constant at 0.01 significance level but the KS test rejects this null hypothesis at 0.05 significance level.

4. Conclusion

The GIC and DLC analyses gave us the clearer picture of how inequality in Thailand is changing. We can see the difference between two time periods, 2013–2019 and 2019–2021. Changes in Gini coefficients of both periods convinced us that inequality in Thailand is slightly improving, however the GIC and DLC analyses gave different stories between both periods. During 2013–2019, the low quantile households have positive income growth while the high quantile households have negative income growth. The inequality improved in the better direction but it could not reach the level that it should be as shown by its counterfactual curves. During 2019–2021, we did not see any significant changes in income growth of every household. The counterfactual curves instead showed that low quantile households should have positive income growth and high quantile households should have negative income growth. Moreover, the counterfactual DLC also showed that Thailand's inequality could be lower than it was. This is contributed to the unobservable covariates or the change in structural of Thai economy such as the effect of COVID-19 to Thai economy.

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