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by

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January 2025
Discussion Paper
No. 227

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 the 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 can we analyze changes in income distribution through 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 changes in Thailand's inequality were different in these two time periods. There were heterogeneous income growths that reduced Thailand's income inequality during 2013–2019. The improvement mainly comes from the structure effect, not the composition effect. On the other hand, the income growth incidences of middle- and upper-middle-income households worsened in 2019–2021. This caused a slight increase in income inequality, and it contributed to the structure effect as well. The impact of the government's assistance programs is evaluated in both periods. The study found that these programs benefit lower quantile households more than upper quantile households, and hence they reduce income inequality effectively.

Keywords: Growth Incidence Curve, Delta Lorenz 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)).

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), Jaitiang, Huang, and Yang (2021), Karim (2021), Puttanapong, Luenam, and Jongwattanakul (2022), and Sangkasem and Puttanapong (2022)).

Much research on the income distribution of Thailand focuses on inequality and its determination (Paweenawat and McNown (2014), Vanitcharearnthum (2019), Thepsumroeng (2019)). These papers explored Thailand's inequality in different aspects using different methods and data sets. Paweenawat and McNown (2014) focus on examining the determinants of income inequality in Thailand using a synthetic cohort analysis. By using the data from the Thailand Socioeconomic Survey to construct synthetic cohorts, they found that higher levels of education are associated with lower income inequality, which directly benefits policymakers. A similar study was done by Thepsumroeng (2019). Thepsumroeng (2019) studied the dynamics of income inequality in Thailand over the period from 2009 to 2017, using the Gini coefficient as a measure of inequality and household-level data. On the other hand, Vanitcharearnthum (2019) focuses on examining top income shares and their impact on inequality in Thailand. He analyzed the concentration of income among the top earners in Thailand, compared the top income shares over time, and assessed their relationship with overall income inequality. The findings highlight the growing concentration of income among the highest-income earners and their contribution to overall inequality in the country.

Another important aspect of inequality is looking into the interrelationships between inequality, poverty, and economic growth (Kakwani (2000), Deolalikar (2003), Kurita and Kurosaki (2011), Yang, Wang, and Dewina (2020)). Kakwani (2000) provided a comprehensive analysis of poverty dynamics by examining the contributions of economic growth and income inequality to changes in poverty over time. 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. Similarly, Deolalikar (2003) also focuses on examining the relationship between poverty, economic growth, and income inequality in Thailand. The analysis demonstrates that while Thailand has experienced significant economic growth, poverty reduction has not been uniform, and income inequality has persisted. 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 and examines the factors that drive these variations. Recently, Yang, Wang, and Dewina (2020) assessed 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.

Instead of looking at what causes income inequality, many researchers studied the impact of government policies or the change in economic structure to the income distribution (Son (2004), Piet and Desjeux (2021), Suwanprasert (2024)). The concept of pro-poor growth policy was studied by Son (2004). Son (2004) 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 impact of the Common Agricultural Policy (CAP) of the European Union (EU) to the distribution of farm incomes of French commercial farms between 2000 and 2007 was studied by Piet and Desjeux (2021). They also employ the method of Ferreira, Firpo, and Galvao (2019) to examine each quantile of the distribution rather than only the summary statistic such as the Gini coefficient. They found that CAP payments can level off income inequalities. A change in economic structure can cause a change in income distribution as well. Suwanprasert (2024) studied the effect of Thailand's 2014 military coup on Thailand's income distribution using the synthetic control method. Considering summary statistics such as the Gini coefficient and the income quantile share ratio, Suwanprasert (2024) did not find any evidence of the effects of Thailand's 2014 military coup on Thailand's income distribution.

Measuring inequalities from a given distribution is quite a technical challenge. Many researchers conveniently use summary statistics such as the Gini coefficient or quantile share ratio to measure inequalities. However, these are just summary statistics; they did not give researchers the full details of the distribution. For example, a decrease in Gini coefficient means an inequality improvement but this statistic does not tell where the improvement comes from. It could be because the rich has lower or negative income growth, or the poor has higher income growth, or both. But by analyzing the whole distribution, not only a researcher can answer the previous questions but one also can tell the proportion of those population who has higher or lower income growth. Moreover, one can decompose the distributional change into the composition effect and structural effect. This decomposition can show a researcher that an inequality improvement comes from changes in composition of the observed covariates or the economic structural change over that period. Better understanding of composition effect and structural effect can lead to a policy design. Furthermore, distributional changes can be used for deeper policy evaluation. Not only we can conclude whether the policy improves income inequality, but also the distributional analysis can tell the researcher whether the policy hits the right target and what proportion of the population is impacted by the policy. Therefore, by analyzing any quantile of the distribution, researchers can see a clearer picture of how income distribution changes. Since many inequality measures are calculated from the Lorenz curve, estimating Lorenz curves is of main interest to many researchers in this field (Chotikapanich (1993), Sitthiyot and Holasut (2021), Sitthiyot and Holasut (2023), Ferreira, Firpo, and Galvao (2019)).

Many researches used parametric approach to estimating the Lorenz curve. This can be done by fitting the Lorenz curve with a parametric distribution such as a beta distribution or a gamma distribution. Chotikapanich (1993) examined the characteristics and properties of various functional forms, including the beta, gamma, and Singh-Maddala forms, and assessed their suitability for representing income inequality. Sitthiyot and Holasut (2021) proposed an alternative parametric functional form for estimating the Lorenz curve that could fit well with the actual income distribution data which in turn could be useful for policy analysis.

The main objective of this study is to analyze the shifts in Thailand's income distribution from 2013 to 2021. To fully understand the changes as mentioned earlier, instead of analyzing the summary statistics, this paper will analyze the entire distribution by looking into two key estimates: 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, provides insights into the cumulative change in income share up to each quantile $\alpha \in (0, 1)$ of the distribution. By utilizing these curves, we aim to provide a comprehensive understanding of income distribution dynamics in the country.

The GIC and DLC can also be used to evaluate a government's policy impact (Piet and Desjeux (2021)). In this paper, we also want to explore the redistributive impact of the social assistance program. In this paper, we assessed the impact of the social assistance program by analyzing the difference-in-difference of the GICs and DLCs. 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.

Changes in income distribution can be decomposed into the composition effect and the structure effect, the composition effect is the change in income distribution from the observable covariates, and the structure effect is the change in income distribution from the unobservable covariates or from the change in economic structure. The weighted quantile regression method proposed by Ferreira, Firpo, and Galvao (2019) can be easily applied to analyze this decomposition.

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. This paper focuses on Thailand's income distribution during 2013–2021. Because changes in economic structure can possibly have a huge impact on income distribution, we can study their impacts through the structural effect decomposed from changes in income distribution. There were two important changes in economic structure in Thailand during 2013–2021. The first is Thailand's military coup in 2014. Changes in political regime undoubtedly change economic structure and hence the income distribution. The second is the COVID-19 pandemic which hits Thailand severely in 2020. Many businesses were forced to shut down to prevent close contact and spreading of diseases. This is obviously impact the economic structure and the income distribution. Therefore, in this paper, we split our analysis into two periods: 2013–2019 and 2019–2021, because of different changes in economic structure in those two periods. The period 2013–2019 covered 2014 Thailand's military coup, which might have a significant structure effect on income distribution (Suwanprasert (2024)). The period 2019–2021 covered the COVID-19 pandemic, which is another structure effect on income distribution.

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.

The remainder of the paper is structured as follows. Section 2 provides the model and methodology proposed by Ferreira, Firpo, and Galvao (2019). Section 3 describes the data used in this study and the hypothesis testing procedures. Section 4 discusses the changes in Thailand's income distribution using GICs and DLCs and analyzes the impact of social assistance programs on Thailand's income distribution for the period 2013–2019. Section 5 discusses the changes in Thailand's income distribution using GICs and DLCs and analyzes the impact of social assistance programs on Thailand's income distribution for the period 2019–2021. Section 6 concludes.

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,

$$\gamma = \frac{\mu_1}{\mu_0} - 1, \tag{1}$$

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

Another approach to studying 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

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

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,

$$G_t = 1 - 2\int_0^1 L_t(\alpha) d\alpha. \tag{3}$$

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 in 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 do not give a picture of the evolution of the whole income distribution. 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,

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

provided that $q_0(\alpha) \neq 0$. The GIC can be used for income inequality comparison but not for the study of individual movement over time because any individual could be at a different quantile at a 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, $\bar{\gamma} = \int_0^1 GIC(\alpha)d\alpha$.

For 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,

$$DLC(\alpha) = L_1(\alpha) - L_0(\alpha). \tag{5}$$

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*, while 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 a 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 $X = (X_1, \ldots, X_d)$ does not change. Hence, the change in income distribution can be decomposed as

$$F_{Y1}(y) - F_{Y0}(y) = \big(F_{Y1}(y) - F^*_{Y1}(y)\big) + \big(F^*_{Y1}(y) - F_{Y0}(y)\big). \tag{6}$$

The first term $F_{Y1}(y) - F^*_{Y1}(y)$ represents the change in income distribution caused by a change in the 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, 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

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

where $F_{Y1|X1}$ 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 a counterfactual analysis of the change in income distribution by using the counterfactual distribution instead of the factual 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

$$DLC^*(\alpha) = L^*_1(\alpha) - L_0(\alpha), \tag{9}$$

where $L^*_1(\alpha) = \int_0^\alpha \frac{q^*_1(a)}{\mu^*_1}da$ is the counterfactual Lorenz curve and $\mu^*_1 = \int_{-\infty}^{+\infty} ydF^*_{Y1}(y)$ 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 $G^*_1 = 1 - 2\int_0^1 L^*_1(\alpha)d\alpha$ is the counterfactual Gini coefficient of period $t = 1$.

2.2 Estimation and Inference

Since the true income distribution F_{Y1} and F_{Y0} are unknown in practice, every functions and their related quantities mentioned in the previous subsection must be consistently estimated from the data. Ferreira et al. (2019) showed that all the quantile functions, both factual and counterfactual ones, can be estimated by using the weighted quantile regression framework introduced by Koenker and Bassett (1978).

Let $p(X)$ be the (unknown) conditional probability of being observed at period 1 given X, and p be its (unknown) 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 of being observed at period 1.

The quantile functions are estimated by using the weighted quantile regressions,

$$Y_{it} = \beta_0 + \varepsilon_{it}, \quad i = 1, \ldots, n_t;\ t = 0, 1, \tag{10}$$

where Y_{it} is the income of household i at period t and ε_{it} is the error term satisfying all standard quantile regression assumptions. By using $\hat{w}_{1i} = T_1/\hat{p}$, $\hat{w}_{0i} = (1 - T_i)/(1 - \hat{p})$, and $\hat{w}^*_{1i} = \left(\frac{1-\hat{p}(X_i)}{1-\hat{p}(X_i)}\right)\left(\frac{T_i}{1-\hat{p}}\right)$ as the weights of each observation for the quantile regression, Ferreira et al. (2019) showed that the estimated intercepts are the quantile estimators $\hat{q}_1(\alpha)$, $\hat{q}_0(\alpha)$, and $\hat{q}^*_1(\alpha)$, respectively.

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

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

$$\widehat{GIC}^*(\alpha) = \frac{\hat{q}^*_1(\alpha)}{\hat{q}_0(\alpha)} - 1. \tag{12}$$

The factual and counterfactual Lorenz curves, the factual 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 factual and counterfactual GIC estimators can be derived using the delta method.

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

$$H_0:\ \beta(\alpha) - r(\alpha) = 0 \text{ uniformly for all } \alpha. \tag{13}$$

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,

$$KS = \sqrt{n} \sup_{\alpha} \left| \hat{\beta}(\alpha) - r(\alpha) \right|, \tag{14}$$

or the Cramér-von Mises type test statistic,

$$CvM = \sqrt{n} \int_0^1 \left| \hat{\beta}(\alpha) - r(\alpha) \right| d\alpha. \tag{15}$$

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 $r(\alpha)$ by its estimate $\hat{r}(\alpha)$. The critical values of these tests can be obtained by using the recentered bootstrap procedure.

3 Data and Empirical Procedures

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 households.

The study period covers a period of seven years before and after 2014 Thailand's military coup (2013–2019) and three years during the COVID-19 pandemic (2019–2021). The unit of analysis of income distribution is 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 are 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 the household head is female), marital status dummy ($Married = 1$ if the household head is married), and agricultural sector dummy

($Agriculture = 1$ if the primary or secondary occupation of household head is in the agricultural sector). Regional dummies are also included in the logit regression analysis. Households with missing values in any of these variables are omitted from the sample. This paper is restricted to the case where the age of the household head is between 16 and 65 years old; the household must have a positive income, and the share of government assistance is in the close unit interval $[0, 1]$. Finally, the top and bottom 0.5% of the income variable are trimmed off to reduce outliers.

3.2 Empirical Procedures

Let the observable covariates (X) be the age of household head and its squared, years of schooling of the household head and its squared, rural dummy variable, gender dummy variable, marital status dummy variable, agricultural sector dummy variable, and regional dummy variables. These variables are used in the logit regression to predict the propensity score for being observed in the later period $\hat{p}(X)$.

For income with government assistance included, we estimate the quantile of income distribution for each $\alpha = 0.01, 0.02, \ldots, 0.99$. Then we estimate the growth incidence curve $\widehat{GIC}(\alpha)$ and its counterfactual $\widehat{GIC}^*(\alpha)$, and the delta Lorenz curve $\widehat{DLC}(\alpha)$ and its counterfactual $\widehat{DLC}^*(\alpha)$. The following six hypotheses are tested.

Test 1: Static distribution.

Testing $H_0: \; GIC(\alpha) = 0 \; \forall \alpha \in (0, 1)$ vs $H_A: \; GIC(\alpha) \neq 0 \; \exists \alpha \in (0, 1)$.

Test 2: Distributional-neutral growth.

Testing $H_0: \; GIC(\alpha) = \bar{\gamma} \; \forall \alpha \in (0, 1)$ vs $H_A: \; GIC(\alpha) \neq \bar{\gamma} \; \exists \alpha \in (0, 1)$.

Test 3: Constant inequality.

Testing $H_0: \; DLC(\alpha) = 0 \; \forall \alpha \in (0, 1)$ vs $H_A: \; DLC(\alpha) \neq 0 \; \exists \alpha \in (0, 1)$.

Test 4: Static counterfactual distribution.

Testing $H_0: \; GIC^*(\alpha) = 0 \; \forall \alpha \in (0, 1)$ vs $H_A: \; GIC^*(\alpha) \neq 0 \; \exists \alpha \in (0, 1)$.

Test 5: Counterfactual distributional-neutral growth.

Testing $H_0: \; GIC^*(\alpha) = \bar{\gamma}^* \; \forall \alpha \in (0, 1)$ vs $H_A: \; GIC^*(\alpha) \neq \bar{\gamma}^* \; \exists \alpha \in (0, 1)$.

Test 6: Constant counterfactual inequality.

$$\text{Testing } H_0: \ DLC^*(\alpha) = 0 \ \forall \alpha \in (0,1) \text{ vs } H_A: \ DLC^*(\alpha) \neq 0 \ \exists \alpha \in (0,1).$$

We begin by examining the hypothesis that income distribution has remained entirely unchanged. This is done by testing whether the GIC is identically zero across all quantiles (Test 1). A rejection of this null hypothesis would indicate that some level of income redistribution has occurred. Following this, we proceed to evaluate whether the change in income distribution are uniformly across quantiles (Test 2). This is for determination whether income shifts have been equitable across quantiles. We apply a similar approach to the delta Lorenz curve by investigating whether there is a change in Thailand's income inequality (Test 3). Rejecting this null hypothesis implies that there was a change in Thailand's income inequality in that period.

We apply the previous testing procedures to the estimated counterfactual income distribution as well. Recall that the counterfactual GIC and counterfactual DLC represent the structural effect on income distribution. Thus we first would like to test whether there is a significant structural effect on the income distribution. This is done by testing whether counterfactual GIC is identically zero across all quantiles (Test 4). A rejection of this null hypothesis suggests there is a structural effect on Thailand's income distribution. Next we would like to test whether this structural changes on income growth impact each quantile equally. This is done by testing whether the counterfactual GIC is uniform across quantiles (Test 5). Rejection of this null hypothesis implies that the structural effects are inequitable across quantiles. Similarly, we use the similar approach to the estimated counterfactual DLC to determine whether structural change effects the income inequality (Test 6). Rejecting this null hypothesis implies that the structural effect changes Thailand's income inequality in that period.

For income without government assistance, we estimate the quantile of income distribution for each $\alpha = 0.01, 0.02, \ldots, 0.99$. Then we estimate the growth incidence curve $\widehat{GIC}_0(\alpha)$ and its counterfactual $\widehat{GIC}^*_0(\alpha)$, and the delta Lorenz curve $\widehat{DLC}_0(\alpha)$ and its counterfactual $\widehat{DLC}^*_0(\alpha)$. The following six hypotheses are tested.

Test 7: Static distribution.

$$\text{Testing } H_0: \ GIC_0(\alpha) = 0 \ \forall \alpha \in (0,1) \text{ vs } H_A: \ GIC_0(\alpha) \neq 0 \ \exists \alpha \in (0,1).$$

Test 8: Distributional-neutral growth.

Testing $H_0: \ GIC_0(\alpha) = \bar{\gamma}_0 \ \forall\alpha \in (0,1)$ vs $H_A: \ GIC_0(\alpha) \neq \bar{\gamma}_0 \ \exists\alpha \in (0,1)$.

Test 9: Constant inequality.

Testing $H_0: \ DLC_0(\alpha) = 0 \ \forall\alpha \in (0,1)$ vs $H_A: \ DLC_0(\alpha) \neq 0 \ \exists\alpha \in (0,1)$.

Test 10: Static counterfactual distribution.

Testing $H_0: \ GIC_0^*(\alpha) = 0 \ \forall\alpha \in (0,1)$ vs $H_A: \ GIC_0^*(\alpha) \neq 0 \ \exists\alpha \in (0,1)$.

Test 11: Counterfactual distributional-neutral growth.

Testing $H_0: \ GIC_0^*(\alpha) = \bar{\gamma}_0^* \ \forall\alpha \in (0,1)$ vs $H_A: \ GIC_0^*(\alpha) \neq \bar{\gamma}_0^* \ \exists\alpha \in (0,1)$.

Test 12: Constant counterfactual inequality.

Testing $H_0: \ DLC_0^*(\alpha) = 0 \ \forall\alpha \in (0,1)$ vs $H_A: \ DLC_0^*(\alpha) \neq 0 \ \exists\alpha \in (0,1)$.

The rationals of these six hypotheses are the same as the first tested six hypotheses, however, these six hypotheses testings are analyzing changes in income distribution and the structural effects if government assistant is excluded from households' income.

Moreover, by using the difference-in-difference idea, we can analyze the policy impact of the government assistance program to the income distribution by evaluating the difference of GICs when the income includes and excludes government assistance and the difference of DLCs when the income includes and excludes government assistance. Define the factual and counterfactual GIC difference (ΔGIC and ΔGIC^*) and factual and counterfactual DLC difference (ΔDLC and ΔDLC^*) as

$$\Delta GIC(\alpha) = GIC(\alpha) - GIC_0(\alpha), \tag{16}$$

$$\Delta GIC^*(\alpha) = GIC^*(\alpha) - GIC_0^*(\alpha), \tag{17}$$

$$\Delta DLC(\alpha) = DLC(\alpha) - DLC_0(\alpha), \tag{18}$$

$$\Delta DLC^*(\alpha) = DLC^*(\alpha) - DLC_0^*(\alpha). \tag{19}$$

The factual GIC difference (ΔGIC) can be interpreted as the policy impact on the income growth of each quantile in the distribution. The counterfactual GIC difference (ΔGIC^*) shows the policy impact on the counterfactual income growth of each quantile in the distribution. The factual DLC difference (ΔDLC) represents the policy impact on the income inequality the income distribution, and finally the counterfactual DLC difference (ΔDLC^*) tells the policy impact on the counterfactual income inequality of the income distribution.

Thus we estimate the policy impact of the government assistance program to the income distribution by estimating these differences in GICs and DLCs straightforwardly as follow.

$$
\begin{aligned}
\Delta\widehat{GIC}(\alpha) &= \widehat{GIC}(\alpha) - \widehat{GIC}_0(\alpha), && (20)\\
\Delta\widehat{GIC}^*(\alpha) &= \widehat{GIC}^*(\alpha) - \widehat{GIC}_0^*(\alpha), && (21)\\
\Delta\widehat{DLC}(\alpha) &= \widehat{DLC}(\alpha) - \widehat{DLC}_0(\alpha), && (22)\\
\Delta\widehat{DLC}^*(\alpha) &= \widehat{DLC}^*(\alpha) - \widehat{DLC}_0^*(\alpha). && (23)
\end{aligned}
$$

After we estimate those policy impacts, first we would like to examine whether the government assistance program has any impact on factual and counterfactual income distributions. This can be done by testing whether ΔGIC is zero across quantiles (Test 13). Rejection of this null hypothesis implies that the policy impacts some quantiles of factual income distribution. Then we would like to test whether whether the government assistance program has any impact on counterfactual income distribution. This can be done by testing whether ΔGIC^* is zero across quantiles (Test 14). Rejection of this null hypothesis shows that the policy impacts some quantiles of counterfactual income distribution. Finally we would like to investigate whether the government assistance program has any impact on factual and counterfactual income inequalities. This can be done by testing whether ΔDLC is zero across quantiles (Test 15). Rejection of this null hypothesis implies that the policy impacts factual income inequality of Thailand. Lastly we would like to test whether whether the government assistance program has any impact on counterfactual income inequality. This can be done by testing whether ΔDLC^* is zero across quantiles (Test 16). Rejection of this null hypothesis shows that the policy impacts counterfactual income inequality. Therefore, we test the following four hypotheses.

Test 13: No policy impact on income distribution.

Testing $H_0:\ \Delta GIC(\alpha) = 0\ \forall\alpha \in (0,1)$ vs $H_A:\ \Delta GIC(\alpha) \neq 0\ \exists\alpha \in (0,1)$.

Test 14: No policy impact on counterfactual income distribution.

Testing $H_0:\ \Delta GIC^*(\alpha) = 0\ \forall\alpha \in (0,1)$ vs $H_A:\ \Delta GIC^*(\alpha) \neq 0\ \exists\alpha \in (0,1)$.

Test 15: No policy impact on inequality.

Testing $H_0: \Delta DLC(\alpha) = 0 \ \forall \alpha \in (0,1)$ vs $H_A: \Delta DLC(\alpha) \neq 0 \ \exists \alpha \in (0,1)$.

Test 16: No policy impact on counterfactual inequality.

Testing $H_0: \Delta DLC^*(\alpha) = 0 \ \forall \alpha \in (0,1)$ vs $H_A: \Delta DLC^*(\alpha) \neq 0 \ \exists \alpha \in (0,1)$.

All these hypotheses testings will shed some lights for us to better understand the income growth, income inequality, and the policy impacts of Thailand over those studied periods.

4 GIC and DLC of Thailand during 2013–2019

The summary statistics of all variables of Thailand in 2013 and 2019 are presented in Table 1.

Year	2013 ($n = 33775$)				2019 ($n = 33545$)			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Income (Govt. Asst. Included)	10157	9561.9	1050	75407	10558	9450.1	1049	75439
Income (Govt. Asst. Excluded)	10083	9565.9	973	75407	10393	9494.5	973	75197
Age	47.01	11.5	16	65	49.01	11.339	16	65
Schooling	7.875	4.7454	0	22	8.216	4.69	0	22
Rural	0.3789	0.4851	0	1	0.4268	0.4946	0	1
Married	0.7027	0.4571	0	1	0.6743	0.4686	0	1
Female	0.3556	0.4787	0	1	0.3861	0.4869	0	1
Agriculture	0.36	0.48	0	1	0.3393	0.4735	0	1

Table 1: Summary statistics of all variables of Thailand in 2013 and 2019.

From Table 1, when government assistance is included, the (sample) mean per capita (real) income of the household increased from 10157 Baht in 2013 to 10558 Baht in 2019. Thus, the estimated growth rate of mean income ($\hat{\gamma}$) between 2013 and 2019 is 0.039 or 3.9%, which is on average equal to 0.65% per year. But when government assistance is excluded, the (sample) mean per capita (real) income of the household increased from 10083 Baht in 2013 to 10393 Baht in 2019. Thus, the estimated growth rate of mean income ($\hat{\gamma}_0$) between 2013 and 2019 is 0.031 or 3.1%, which is on average equal to 0.51% per year. The estimated Gini coefficient decreases from 0.404 in 2013 to 0.3898 in 2019, a decrease of 0.0142.

4.1 Income distribution when government assistance is included

The estimated growth incidence curve ($\widehat{GIC}$) and its estimated counterfactual ($\widehat{GIC}^*$) and the estimated delta Lorenz curve ($\widehat{DLC}$) and its estimated counterfactual ($\widehat{DLC}^*$) are shown in Figures 1 and 2.

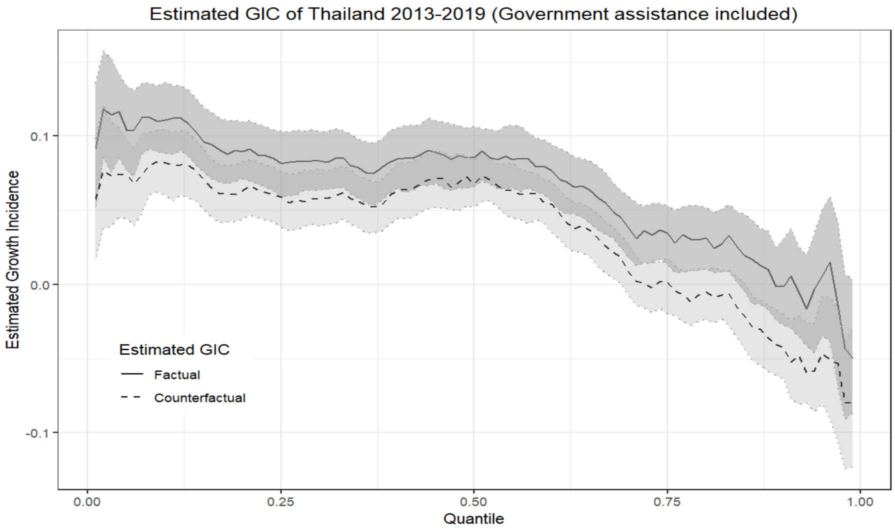

Figure 1: Estimated growth incidence curve and its estimated counterfactual for Thailand 2013–2019 when government assistance is included. The light shaded area represents 95% confidence band of counterfactual GIC. The darker shaded area represents 95% confidence band of factual GIC. The overlapping of two confidence bands create a darkest shaded region.

From Figure 1, the estimated growth incidence decreases from 0.1 to -0.05. The households below the 90$^{\text{th}}$ percentile have positive income growth, but the top ten percent of the households have negative income growth. The estimated average income growth rate ($\hat{\bar{\gamma}}$) is about 0.065 or 6.5%. The estimated counterfactual growth incidence decreases from 0.06 to -0.08. The estimated counterfactual GIC showed that, conditional on the observable covariates, the households below the third quartile have positive income growth and the top 25% of the households have negative income growth. The estimated counterfactual average income growth rate ($\hat{\bar{\gamma}}^*$) is about 0.035 or 3.5%. Since only top quartile had negative growth, this implies the inequality in Thailand was improved during 2013–2019. Moreover, the estimated GIC is uniformly above its estimated counterfactual and they have similar shapes, this implies the income growth was mainly contributed from the structure effect.

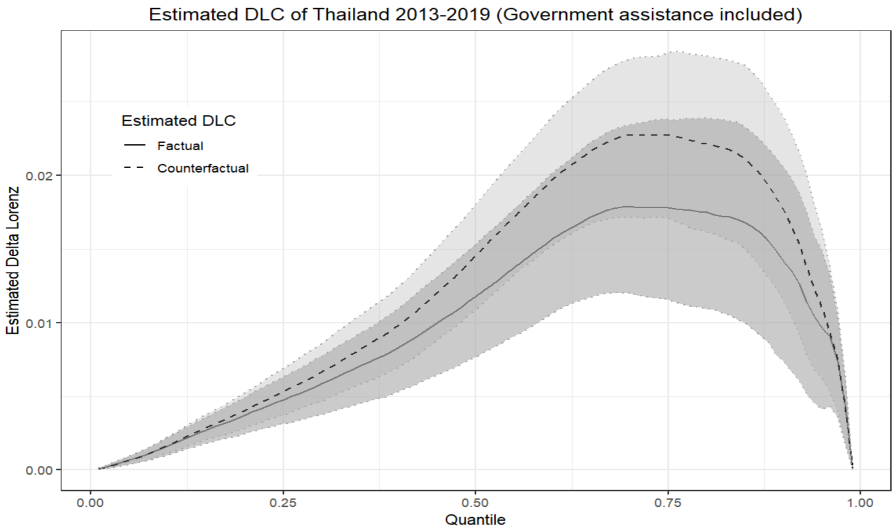

Figure 2: Estimated delta Lorenz curve and its estimated counterfactual for Thailand 2013–2019 when government assistance is included. The light shaded area represents 95% confidence band of counterfactual DLC. The darker shaded area represents 95% confidence band of factual DLC. The overlapping of two confidence bands create a darkest shaded region.

From Figure 2, the estimated DLC is positive at all quantiles and it reaches its maximum of 0.0179 at the 70^{th} percentile. The estimated counterfactual DLC is also positive at all quantiles and it reaches its maximum of 0.0227 at the 71^{st} percentile. Since estimated DLC and its estimated counterfactual are positive everywhere, these mean the income share of the lower quantile households was increased during 2013–2019. The estimated Gini coefficient decreases from 0.4 in 2013 to 0.381 in 2019, a decrease of 0.019. However, the estimated counterfactual Gini coefficient of 2019 is 0.376, which is less than the estimated factual Gini coefficient of 0.381. Thus, the structural effect reduces inequality, but the composition effect offsets this decline. This is confirmed from Figure 2 that the estimated counterfactual DLC is uniformly above the estimated factual DLC.

Hypotheses 1–6 are tested using KS tests and CvM tests of GIC, GIC^*, DLC, and DLC^* are shown in Table 2.

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 and also reject the null hypothesis of constant growth rate at average level at all quantiles at 0.01 significance

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$GIC(\alpha) = 0$	30.678***	14.6	16.3	21.3	17.309***	3.74	4.2	4.91
$GIC(\alpha) = \bar{\gamma}$	29.694***	15.5	17.4	21.9	8.138***	4.01	4.34	5.17
$DLC(\alpha) = 0$	4.637***	1.62	1.85	2.36	2.56***	0.729	0.837	1.121
$GIC^{*}(\alpha) = 0$	21.447***	13.5	15	18	13.085***	3.08	3.48	4.19
$GIC^{*}(\alpha) = \bar{\gamma}^{*}$	29.694***	14	15.5	18.3	9.716***	3.29	3.6	4.34
$DLC^{*}(\alpha) = 0$	5.9***	1.5	1.75	2.24	3.139***	0.663	0.778	1.045

Table 2: The hypothesis testing results of Thailand 2013–2019 (government assistance included). *** denotes statistical significance at 1% level.

level. Hence, there is a growth in income of Thai households from 2013 to 2019 and the growth is heterogeneous. Constant inequality hypothesis is rejected by both tests at 0.01 significant level, thus we can conclude that there was a change in income inequality in Thailand during 2013–2019. Conditional on observable covariates, both tests reject the null hypothesis that there is no income growth in all quantiles, reject the null hypothesis of constant growth rate at average level at all quantiles, and reject the null hypothesis of constant inequality at 0.01 significance level. These indicate a strong heterogeneous structure effect of the distributional changes.

4.2 Income distribution when government assistance is excluded

The estimated growth incidence curve ($\widehat{GIC}_0$) and its estimated counterfactual ($\widehat{GIC}_0^{*}$) and the estimated delta Lorenz curve ($\widehat{DLC}_0$) and its estimated counterfactual ($\widehat{DLC}_0^{*}$) are shown in Figures 3 and 4.

From Figure 3, the estimated growth incidence initially increases from 0 to 0.08 around the median and then decreases to -0.05. The households below the 90^{th} percentile have positive income growth, but the top ten percent of the households have negative income growth. The estimated average income growth rate ($\hat{\bar{\gamma}}_0$) is about 0.046 or 4.6%. The estimated counterfactual growth incidence increases from -0.02 to 0.065 around the median and then decreases to -0.08. The estimated counterfactual GIC showed that, conditional on the observable covariates, the households below the third quartile have positive income growth and the top 25% of the households have negative income growth. The estimated counterfactual average income growth

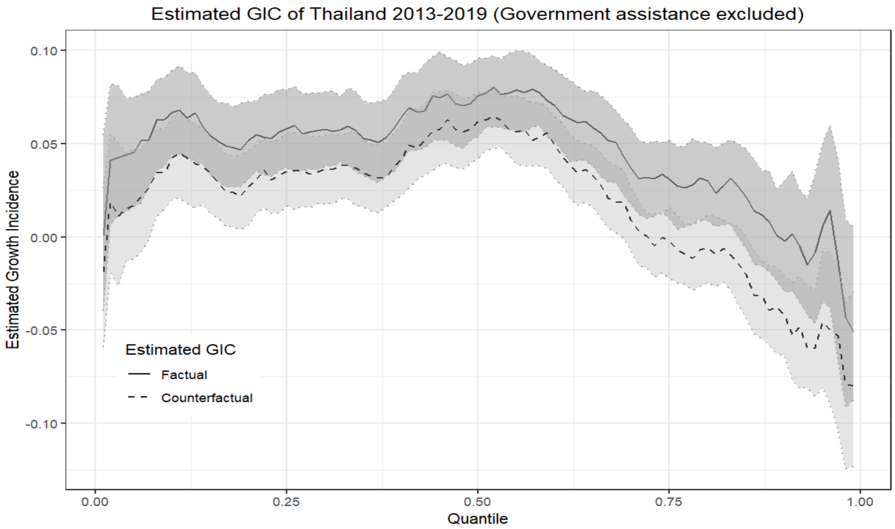

Figure 3: Estimated growth incidence curve and its estimated counterfactual for Thailand 2013–2019 when government assistance is excluded. The light shaded area represents 95% confidence band of counterfactual GIC. The darker shaded area represents 95% confidence band of factual GIC. The overlapping of two confidence bands create a darkest shaded region.

rate ($\hat{\bar{\gamma}}_0^*$) is about 0.019 or 1.9%. Since only top quartile had negative growth, this implies that, without government assistance, the inequality in Thailand was improved during 2013–2019. Moreover, the estimated GIC is uniformly above its estimated counterfactual and they have similar shapes, this implies the income growth was mainly contributed from the structure effect.

From Figure 4, the estimated DLC is positive at the third percentile and above and it reaches its maximum of 0.0143 at the third quartile. The estimated counterfactual DLC is also positive at the second percentile and above and it reaches its maximum of 0.0195 at the third quartile. Since estimated DLC and its estimated counterfactual are positive almost everywhere, these mean that, without government assistance, the income share of the lower quantile households was increased during 2013–2019. The estimated Gini coefficient decreases from 0.4 in 2013 to 0.39 in 2019, a decrease of 0.01. However, the estimated counterfactual Gini coefficient of 2019 is 0.385, which is less than the estimated factual Gini coefficient of 0.39. Thus, the structural effect reduces inequality, but the composition effect offsets this decline. This is confirmed from Figure 4 that the estimated counterfactual DLC is uniformly above the estimated factual DLC.

Hypotheses 7–12 are tested using KS tests and CvM tests of GIC_0, GIC_0^*, DLC_0, and DLC_0^*

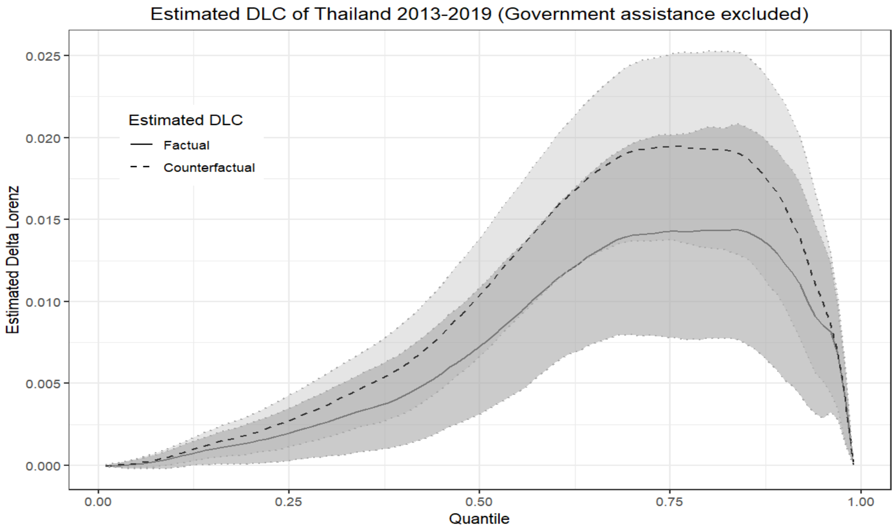

Figure 4: Estimated delta Lorenz curve and its estimated counterfactual for Thailand 2013–2019 when government assistance is excluded. The light shaded area represents 95% confidence band of counterfactual DLC. The darker shaded area represents 95% confidence band of factual DLC. The overlapping of two confidence bands create a darkest shaded region.

are shown in Table 3.

From Table 3 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 and also reject the null hypothesis of constant growth rate at average level at all quantiles at 0.01 significance level. Hence, without government assistance, there is a growth in income of Thai households from 2103 to 2019 and the growth is heterogeneous. Constant inequality hypothesis is rejected by both

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$GIC_0(\alpha) = 0$	20.823**	14.9	17	21.7	12.513***	3.78	4.22	5.04
$GIC_0(\alpha) = \bar{\gamma}_0$	25.107***	15.6	18	22.2	5.423***	4.04	4.38	5.35
$DLC_0(\alpha) = 0$	3.729***	1.6	1.86	2.41	1.817***	0.726	0.823	1.148
$GIC_0^*(\alpha) = 0$	20.684***	13.4	15	18.4	9.089***	3.11	3.52	4.22
$GIC_0^*(\alpha) = \bar{\gamma}_0^*$	25.496***	13.9	15.4	18.1	7.304***	3.33	3.66	4.37
$DLC_0^*(\alpha) = 0$	5.053***	1.53	1.74	2.3	2.455***	0.655	0.773	1.054

Table 3: The hypothesis testing results of Thailand 2013–2019 (government assistance excluded). ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

tests at 0.01 significant level, thus we can conclude that, without government assistance, there was a change in income inequality in Thailand during 2013–2019. Conditional on observable covariates, both tests reject the null hypothesis that there is no income growth in all quantiles, reject the null hypothesis of constant growth rate at average level at all quantiles, and reject the null hypothesis of constant inequality at 0.01 significance level. These indicate that, without government assistance, there is a strong heterogeneous structure effect of the distributional changes.

4.3 Policy Impact on Income distribution

To analyze the policy impact on income distribution, we compare the GICs and DLCs of Thailand when government assistance is included and excluded. Figures 5 and 6 illustrated the estimates of the difference of the GICs ($\Delta\widehat{GIC}$ and $\Delta\widehat{GIC}^*$) and the estimates of the difference of the DLCs ($\Delta\widehat{DLC}$ and $\Delta\widehat{DLC}^*$).

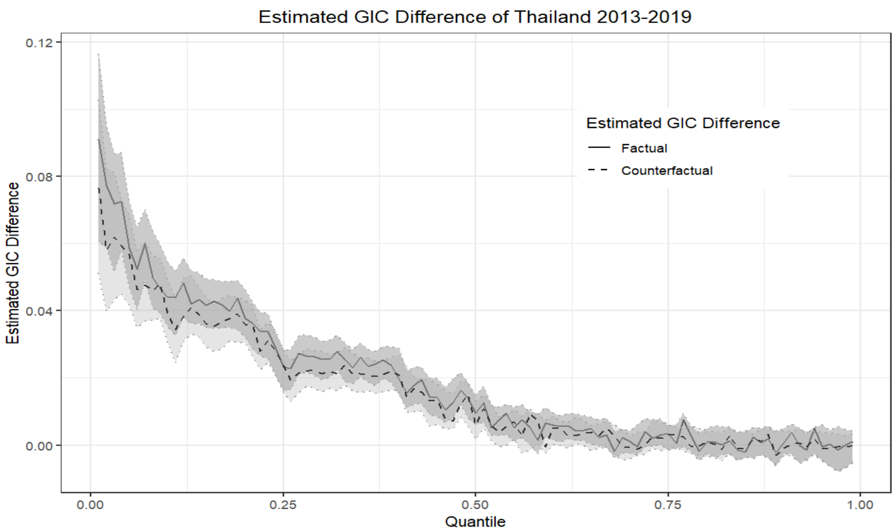

Figure 5: Estimated difference of growth incident curves and its estimated counterfactual for Thailand 2013–2019. The light shaded area represents 95% confidence band of counterfactual GIC difference. The darker shaded area represents 95% confidence band of factual GIC difference. The overlapping of two confidence bands create a darkest shaded region.

From Figure 5, the estimated difference of the growth incidence curves is decreasing. This indicates the government assistance programs benefit the lower quantile households more than the higher quantile households. The estimated difference of the counterfactual growth incidence curves looks very similar to the estimated difference of the factual growth incidence curves, this confirms that the policy has high impact on the structure effect, it has little influence on the composition effect.

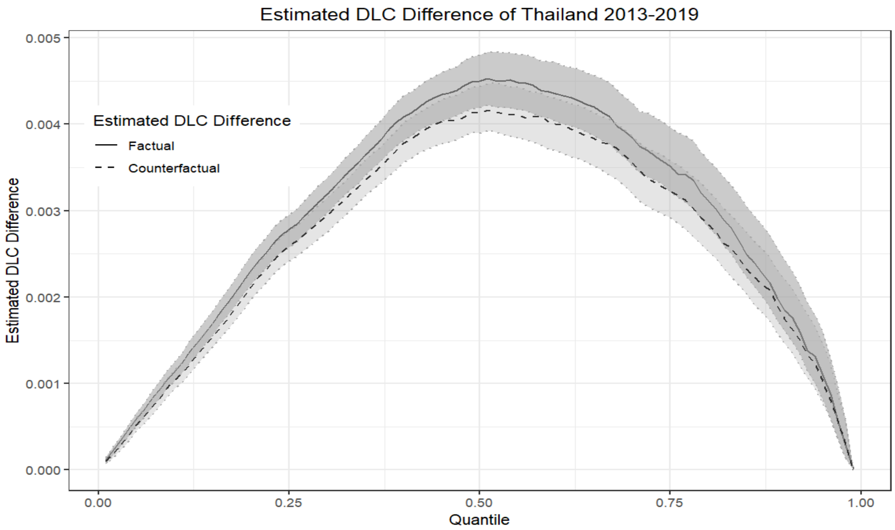

Figure 6: Estimated difference of delta Lorenz curves and its estimated counterfactual for Thailand 2013–2019. The light shaded area represents 95% confidence band of counterfactual DLC difference. The darker shaded area represents 95% confidence band of factual DLC difference. The overlapping of two confidence bands create a darkest shaded region.

From Figure 6 the estimated difference of the factual delta Lorenz curves and the estimated difference of the counterfactual delta Lorenz curves are positive everywhere and they reach the maximum around the median. This also confirms that these policies help the lower quantile households get a higher income share. The estimated difference in factual DLCs and the estimated difference in counterfactual DLCs have similar shape but the estimated difference in factual DLCs is a little higher, these mean the policy mostly impact the structure effect and the policy impact positively to the composition effect cumulatively.

Hypotheses 13–16 are tested using KS tests and CvM tests of ΔGIC, ΔGIC^{*}, ΔDLC, and ΔDLC^{*} are shown in Table 4.

From Table 4 we can see that both KS tests and CvM tests give the same conclusions. Both tests reject the null hypotheses that there is no policy impact on factual and counterfactual income distribution at 0.01 significant level. Hence the government assistance programs improve

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$\Delta GIC(\alpha) = 0$	23.604***	6.35	7.49	9.72	4.877***	0.768	0.799	0.844
$\Delta GIC^{*}(\alpha) = 0$	19.856***	6.39	7.14	8.86	4.229***	0.778	0.803	0.839
$\Delta DLC(\alpha) = 0$	1.175***	0.13	0.152	0.183	0.743***	0.049	0.059	0.074
$\Delta DLC^{*}(\alpha) = 0$	1.079***	0.112	0.126	0.155	0.684***	0.044	0.052	0.066

Table 4: The hypothesis testing results of policy impact on Thailand 2013–2019. $* * *$ denotes statistical significance at 1% level.

Thailand's income distribution during 2013 to 2019. Both tests also reject the null hypotheses that there is no policy impact on factual and counterfactual inequality at 0.01 significant level. Therefore, the government assistance programs reduce Thailand's inequality during 2013–2019.

Despite of Thailand's military coup in 2014, Thailand's income inequality improved gradually. However, the growth is heterogeneous. The lower-quantile households had higher income growth than the higher-quantile households. Government assistant programs in those periods significantly reduced Thailand's income inequality as a structural effect on distribution change. At least half of the population had 5% higher income growth with government assistance. The study suggests that government assistance programs used in those period should be continue because it enhanced income growth to all population, the poor benefited from these programs more than the rich and hence the income inequality was reduced.

5 GIC and DLC of Thailand during 2019–2021

The summary statistics of all variables of Thailand in 2019 and 2021 are presented in Table 5.

From Table 5, when government assistane is included, the (sample) mean per capita (real) income of the household increased from 10558 Baht in 2019 to 10894 Baht in 2021. Thus, the estimated growth rate of mean income ($\hat{\gamma}$) between 2019 and 2021 is 0.032 or 3.2%, which is on average equal to 1.6% per year. But when government assistance is excluded, the (sample) mean per capita (real) income of the household increased from 10393 Baht in 2019 to 10599 Baht in 2021. Thus, the estimated growth rate of mean income ($\hat{\gamma}_0$) between 2019 and 2021 is 0.0198 or 1.98%, which is on average equal to 0.99% per year. The estimated Gini coefficient

Year	2019 ($n = 33458$)				2021 ($n = 33818$)			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
$Income$ (Govt. Asst. Included)	10558	9379.81	1243	73506	10894	9667.84	1243	73720
$Income$ (Govt. Asst. Excluded)	10393	9424.72	1062	73506	10599	9727.71	1063	73389
Age	49.01	11.34	16	65	49.56	11.124	16	65
$Schooling$	8.22	4.69	0	22	8.561	4.679	0	21
$Rural$	0.4264	0.495	0	1	0.4266	0.4946	0	1
$Married$	0.674	0.4688	0	1	0.6639	0.4724	0	1
$Female$	0.3864	0.487	0	1	0.4089	0.4916	0	1
$Agriculture$	0.3383	0.473	0	1	0.3528	0.4779	0	1

Table 5: Summary statistics of all variables of Thailand in 2019 and 2021.

increases from 0.379 in 2019 to 0.3806 in 2021, an increase of 0.0016.

Based on the summary statistics, Thailand had a slow annual income growth rate during 2013–2019 compared to its annual income growth rate during 2019–2021. However, the income inequality is reduced during 2013–2019 but the inequality is worsened during 2019–2021.

5.1 Income distribution when government assistance is included

The estimated growth incidence curve ($\widehat{GIC}$) and its estimated counterfactual ($\widehat{GIC}^*$) and the estimated delta Lorenz curve ($\widehat{DLC}$) and its estimated counterfactual ($\widehat{DLC}^*$) are shown in Figures 7 and 8.

From Figure 7, the estimated growth incidences are positive at all quantiles. It decreases at the beginning from 0.07 to 0.011 around the median; it rebounds to 0.056 around the 84$^{\text{th}}$ percentile and then falls. The estimated average income growth rate ($\hat{\bar{\gamma}}$) is about 0.035 or 3.5%. The estimated counterfactual growth incidence showed similar fluctuations. It decreases from 0.06 to -0.01 then rebounds to 0.017 before dropping to -0.02. The estimated counterfactual average income growth rate ($\hat{\bar{\gamma}}^*$) is about 0.012 or 1.2%. Both estimated GICs showed that the income growth is heterogeneous. The middle income households grew at a smaller rate compared to the low and high income households. Moreover, the estimated factual GIC is uniformly above its counterfactual and they have similar shapes, this implies the income growth

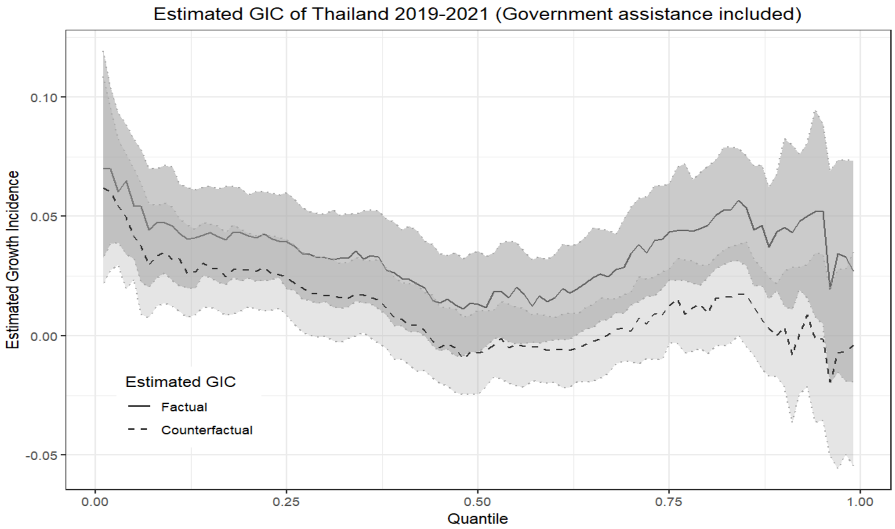

Figure 7: Estimated growth incidence curve and its estimated counterfactual for Thailand 2019–2021 when government assistance is included. The light shaded area represents 95% confidence band of counterfactual GIC. The darker shaded area represents 95% confidence band of factual GIC. The overlapping of two confidence bands create a darkest shaded region.

was mainly contributed from the structure effect.

From Figure 8, the estimated DLC showed little positive until the 45^{th} percentile and then turned negative where its minimum is at the 70^{th} percentile. The estimated counterfactual DLC had similar shape but it is also positive at all quantiles. This shape of the estimated DLC showed that, during 2019–2021, the very low income household gains more share of the income but the middle and upper income households lost a lot of income share. The estimated Gini coefficient increases from 0.379 in 2019 to 0.381 in 2021, an increase of 0.002. However, the estimated counterfactual Gini coefficient of 2021 is 0.375, which is less than the estimated factual Gini coefficient of 0.381. Thus, the structural effect reduces inequality, but the composition effect offsets this decline. This is confirmed from Figure 8 that the estimated counterfactual DLC is uniformly above the estimated factual DLC.

Hypotheses 1–6 are tested using KS tests and CvM tests of GIC, GIC^*, DLC, and DLC^* are shown in Table 6.

From Table 6 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 0.05 significance level

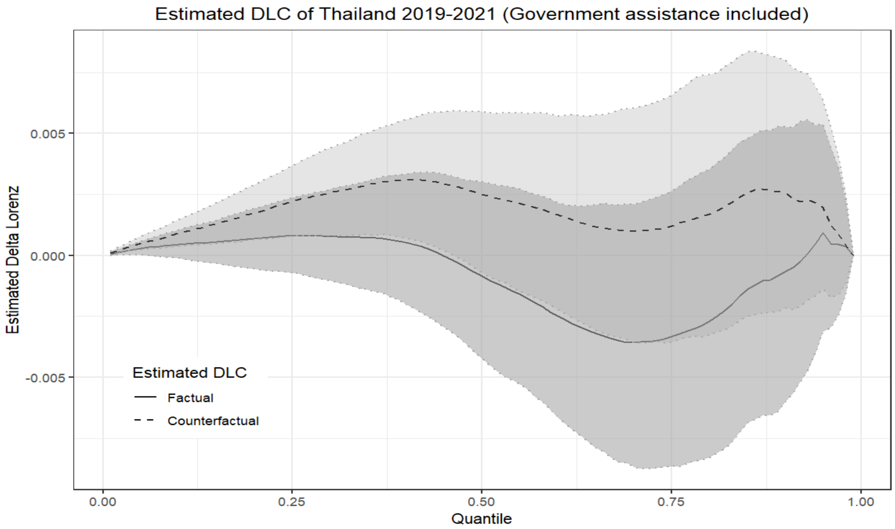

Figure 8: Estimated delta Lorenz curve and its estimated counterfactual for Thailand 2019–2021 when government assistance is included. The light shaded area represents 95% confidence band of counterfactual DLC. The darker shaded area represents 95% confidence band of factual DLC. The overlapping of two confidence bands create a darkest shaded region.

but cannot reject the null hypothesis of constant growth rate at average level at all quantiles. Hence, there is a growth in income of Thai households from 2019 to 2021 and the growth is homogeneous. There was no change in income inequality in Thailand during 2019–2021. Conditional on observable covariates, both tests reject the null hypothesis that there is no income growth in all quantiles, do not reject the null hypothesis of constant growth rate at average level at all quantiles, and do not reject the null hypothesis of constant inequality at 0.01 significance level. These tests indicate a homogeneous structure effect of income growth.

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$GIC(\alpha) = 0$	18.18**	13.7	15.5	18.8	9.065***	3.68	4.18	4.9
$GIC(\alpha) = \bar{\gamma}$	9.023	14.9	16.5	20.1	2.951	3.94	4.34	5.06
$DLC(\alpha) = 0$	0.928	1.46	1.65	2.26	0.329	0.649	0.767	1.059
$GIC^*(\alpha) = 0$	16.105**	13	14.7	16.8	3.833**	2.92	3.25	3.92
$GIC^*(\alpha) = \bar{\gamma}^*$	13.049	13.5	15.2	18.1	3.374*	3.12	3.41	4.04
$DLC^*(\alpha) = 0$	0.801	1.28	1.51	1.95	0.472	0.569	0.703	0.931

Table 6: The hypothesis testing results of Thailand 2019–2021 (government assistance included). *, **, *** denotes statistical significance at 10%, 5%, 1% level, respectively.

5.2 Income distribution when government assistance is excluded

The estimated growth incidence curve ($\widehat{GIC}_0$) and its estimated counterfactual ($\widehat{GIC}_0^*$) and the estimated delta Lorenz curve ($\widehat{DLC}_0$) and its estimated counterfactual ($\widehat{DLC}_0^*$) are shown in Figures 9 and 10.

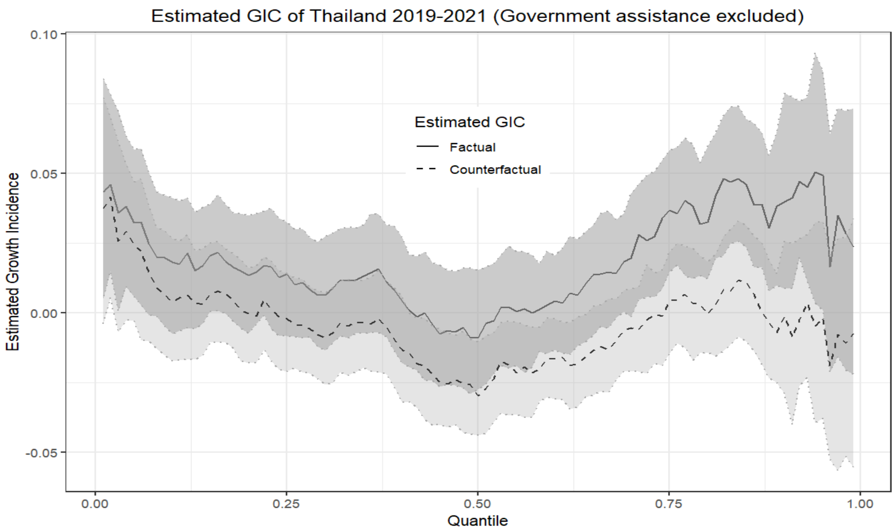

Figure 9: Estimated growth incidence curve and its estimated counterfactual for Thailand 2019–2021 when government assistance is excluded. The light shaded area represents 95% confidence band of counterfactual GIC. The darker shaded area represents 95% confidence band of factual GIC. The overlapping of two confidence bands create a darkest shaded region.

From Figure 9, the estimated growth incidence initially decreases from 0.046 to -0.009 at the median and then increases to 0.048. Except the households around the median, every households have positive income growth. The estimated average income growth rate ($\hat{\bar{\gamma}}_0$) is about 0.02 or 2%. The estimated counterfactual growth incidence decreases from 0.0375 to -0.03 at the median and then rebounds. The estimated counterfactual GIC showed that, conditional on the observable covariates, the households below the first quartile have positive income growth and roughly every other households have negative income growth. The estimated counterfactual average income growth rate ($\hat{\bar{\gamma}}_0^*$) is about -0.004 or -0.4%. Since only households around the median had negative growth, this implies that, without government assistance, the middle income households is worsen during 2019–2021. Moreover, the estimated GIC is uniformly above its estimated counterfactual and they have similar shapes, this implies the income growth was mainly contributed from the structure effect.

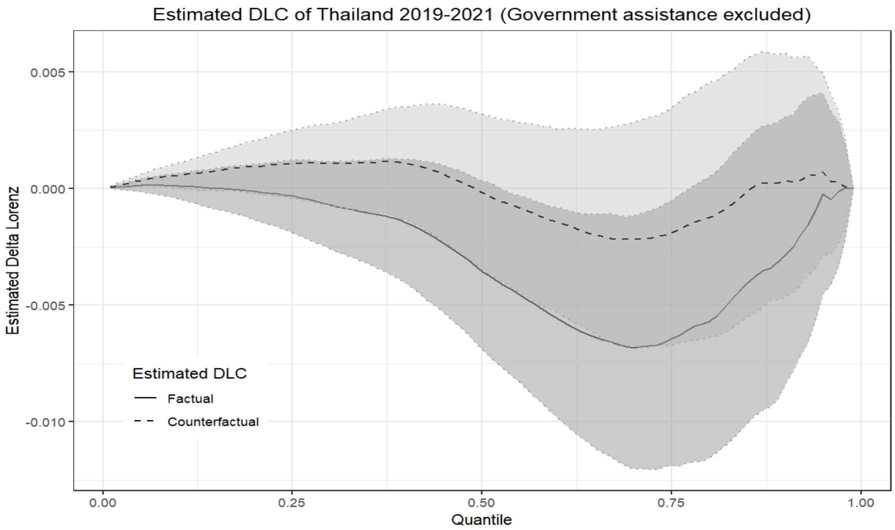

Figure 10: Estimated delta Lorenz curve and its estimated counterfactual for Thailand 2019–2021 when government assistance is excluded. The light shaded area represents 95% confidence band of counterfactual DLC. The darker shaded area represents 95% confidence band of factual DLC. The overlapping of two confidence bands create a darkest shaded region.

From Figure 10, the estimated DLC is negative at the second decile and above and it reaches its minimum of -0.0068 at the 70^{th} percentile. The estimated counterfactual DLC is positive at the beginning then it turned negative after the median and it reached its minimum of -0.0022 at the 7^{th} decile. Since estimated DLC and its estimated counterfactual are negative after the median, these mean that, without government assistance, the income share of the middle and upper-middle quantile households was decreased during 2019–2021. The estimated Gini coefficient increases from 0.3881 in 2019 to 0.3933 in 2021, an increase of 0.0052. However, the estimated counterfactual Gini coefficient of 2021 is 0.3882, which is less than the estimated factual Gini coefficient of 0.3933. Thus, the structural effect reduces inequality, but the composition effect offsets this decline. This is confirmed from Figure 10 that the estimated counterfactual DLC is uniformly above the estimated factual DLC.

Hypotheses 7–12 are tested using KS tests and CvM tests of GIC_0, GIC_0^*, DLC_0, and DLC_0^* are shown in Table 7.

From Table 7 we can see that both KS tests and CvM tests give similar conclusions. CvM test

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$GIC_0(\alpha) = 0$	13.096	13.8	15.4	19.8	5.173***	3.75	4.24	4.93
$GIC_0(\alpha) = \bar{\gamma}_0$	8.161	15	16.6	19.8	3.448	4.03	4.44	5.14
$DLC_0(\alpha) = 0$	1.768**	1.46	1.67	2.22	0.683*	0.661	0.763	1.052
$GIC_0^*(\alpha) = 0$	10.741	12.9	14.2	17.1	2.792	2.97	3.35	3.97
$GIC_0^*(\alpha) = \bar{\gamma}_0^*$	11.772	13.2	15.1	18.2	2.644	3.19	3.49	4.05
$DLC_0^*(\alpha) = 0$	0.567	1.29	1.55	1.99	0.239	0.572	0.695	0.921

Table 7: The hypothesis testing results of Thailand 2019–2021 (government assistance excluded). *, **, *** denotes statistical significance at 10%, 5%, 1% level, respectively.

rejects the null hypothesis that there is no income growth in all quantiles but KS test does not. Both tests do not reject the null hypothesis of constant growth rate at average level at all quantiles but both reject the null hypothesis of constant inequality at 0.1 significance level. Hence, without government assistance, there was a change in income inequality in Thailand during 2019–2021. Conditional on observable covariates, both tests do not reject the null hypothesis that there is no income growth in all quantiles, do not reject the null hypothesis of constant growth rate at average level at all quantiles, and do not reject the null hypothesis of constant inequality at 0.1 significance level. These indicate that, without government assistance, there is no structure effect of the distributional changes.

5.3 Policy Impact on Income distribution

To analyze the policy impact on income distribution, we compare the GICs and DLCs of Thailand when government assistance is included and excluded. Figures 11 and 12 illustrated the estimates of the difference of the GICs ($\Delta\widehat{GIC}$ and $\Delta\widehat{GIC}^*$) and the estimates of the difference of the DLCs ($\Delta\widehat{DLC}$ and $\Delta\widehat{DLC}^*$).

From Figure 11, the estimated difference of the growth incidence curves is decreasing. This indicates the government assistance programs benefit the lower quantile households more than the higher quantile households. The estimated difference of the counterfactual growth incidence curves looks very similar to the estimated difference of the factual growth incidence curves, this confirms that the policy only impacts the structure effect, it has no influence on the composition effect.

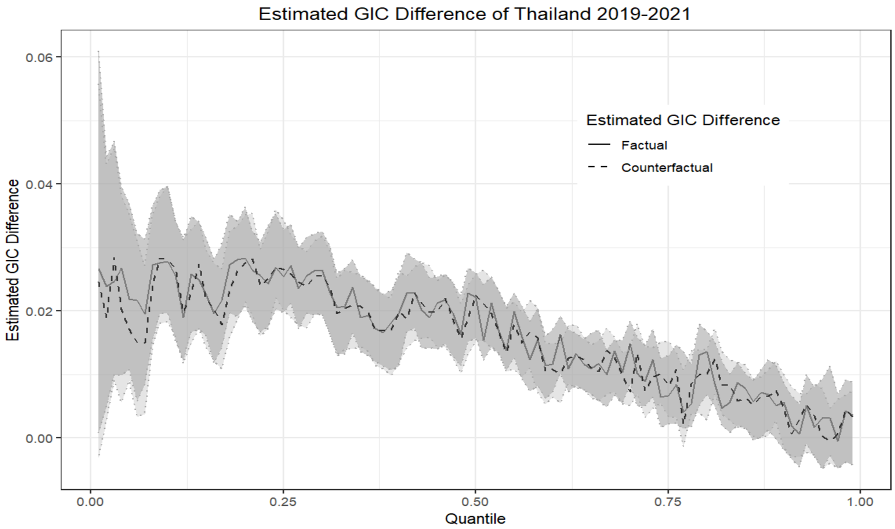

Figure 11: Estimated difference of growth incident curves and its estimated counterfactual for Thailand 2019–2021. The light shaded area represents 95% confidence band of counterfactual GIC difference. The darker shaded area represents 95% confidence band of factual GIC difference. The overlapping of two confidence bands create a darkest shaded region.

From Figure 12 the estimated difference of the factual delta Lorenz curves and the estimated difference of the counterfactual delta Lorenz curves are positive everywhere and they reach the maximum around the 7^{th} decile. This also confirms that these policies help the lower quantile households get a higher income share. The estimated difference in factual DLCs and the estimated difference in counterfactual DLCs have similar shape and they almost overlap each other, these mean the policy only impacts the structure effect, it has no influence on the composition effect.

Hypotheses 13–16 are tested using KS tests and CvM tests of ΔGIC, ΔGIC^*, ΔDLC, and ΔDLC^* are shown in Table 8.

From Table 8 we can see that both KS tests and CvM tests give the same conclusions. Both tests reject the null hypotheses that there is no policy impact on factual and counterfactual income distribution at 0.1 significant level. Hence the government assistance programs improve Thailand's income distribution during 2019 to 2021. Both tests also reject the null hypotheses that there is no policy impact on factual and counterfactual inequality at 0.01 significant level. Therefore, the government assistance programs reduce Thailand's inequality during 2019–2021.

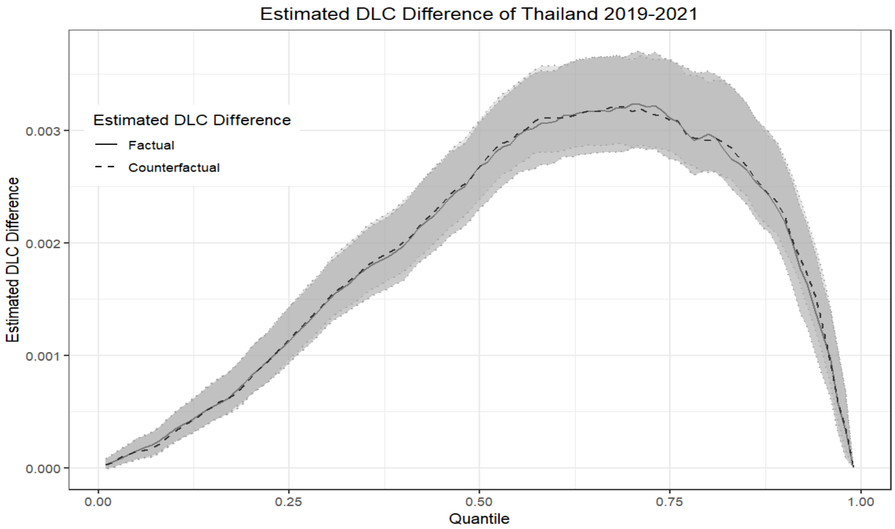

Figure 12: Estimated difference of delta Lorenz curves and its estimated counterfactual for Thailand 2019–2021. The light shaded area represents 95% confidence band of counterfactual DLC difference. The darker shaded area represents 95% confidence band of factual DLC difference. The overlapping of two confidence bands create a darkest shaded region.

Null hypothesis	KS				CvM			
	Test Statistic	10% cv	5% cv	1% cv	Test Statistic	10% cv	5% cv	1% cv
$\Delta GIC(\alpha) = 0$	7.354*	7.02	8.07	10.93	4.183***	0.87	0.905	0.958
$\Delta GIC^{*}(\alpha) = 0$	7.369*	6.98	8.09	10.25	4.049***	0.857	0.884	0.932
$\Delta DLC(\alpha) = 0$	0.841***	0.145	0.165	0.209	0.488***	0.061	0.073	0.099
$\Delta DLC^{*}(\alpha) = 0$	0.836***	0.14	0.153	0.185	0.491***	0.06	0.072	0.093

Table 8: The hypothesis testing results of policy impact on Thailand 2019–2021. * denotes statistical significance at 10% level. *** denotes statistical significance at 1% level.

COVID-19 pandemic started changing Thailand's economic structure in 2020. There was a city lock down. Many businesses is forced to close or temporarily shut down. This affected Thailand's income growth, especially the middle and upper-middle income households. Cumulatively, Thailand's income inequality is worsen. Government implemented some new policies to remedy the problems. These policies significantly helped the income growth of the lower to middle quantile households and hence remedied the worsen income inequality. This study suggests that the policy should be better designed to target the household impacted by the pandemic most.

6 Conclusion

This paper analyzes the changes in Thailand's income distribution in the quantile level during 2013–2021 and the impact of government's assistance programs to Thailand's income distribution. The GIC and DLC analyzes gave us the clearer picture of how inequality in Thailand is changing. We can see the difference of the results between two time periods: 2013–2019 and 2019–2021.

There is a heterogeneous change in Thailand's income distribution during 2013–2019. The lower three quartile households have positive income growth while the top quartile households have negative income growth. The income inequality is improved mainly from the structure effect. Hence, other unobservable covariates or changes in economic structure like 2014 Thailand's military coup could be the cause of inequality improvement. Quantitatively, the growth incidences of low quantile households are higher when they receive some assistance from the government. Policy impact analysis showed that the government's assistance programs hit the correct target and can reduce income inequality. The government assistance programs benefit the lower quantile households more than the higher quantile households. Income inequality is reduced when the households are in the program.

During 2019–2021, we did not see any significant increases in Gini coefficients but there was a significant change in delta Lorenz curve. In this period, the middle and upper-middle income households had small positive or negative income growth rates. They lost their income share more than other households. This is contributed to the unobservable covariates or the change in structure of Thai economy such as the effect of COVID-19 to Thai economy. Similarly, policy impact analysis showed that the government's assistance programs help the lower quantile households more than the higher quantile households. The programs remedy the worsen Thailand's income inequality.

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