Arndt-Corden Department of Economics

Crawford School of Public Policy

ANU College of Asia and the Pacific

Cash subsidies for the poor: Evaluating Thailand's welfare card scheme

Wannaphong Durongkaveroj

Faculty of Economics, Ramkhamhaeng University

Aug 2022

Working Papers in Trade and Development

No. 2022/10

This Working Paper series provides a vehicle for preliminary circulation of research results in the fields of economic development and international trade. The series is intended to stimulate discussion and critical comment. Staff and visitors in any part of the Australian National University are encouraged to contribute. To facilitate prompt distribution, papers are screened, but not formally refereed.

Copies are available at https://acde.crawford.anu.edu.au/acde-research/working-papers-trade-and-development

Cash subsidies for the poor: Evaluating Thailand's welfare card scheme

Wannaphong Durongkaveroj[1]
Faculty of Economics, Ramkhamhaeng University

E-mail address: wannaphong@ru.ac.th

Abstract

This paper examines the poverty-reducing effect of a large-scale unconditional cash transfer program ("the state welfare card scheme") launched by the government of Thailand in 2017 that covers over 20 per cent of the country's population. The program's impact on monetary poverty, measured by consumption expenditure per capita, is estimated using nationally representative household socio-economic survey data collected in 2019. Using a sharp regression discontinuity design, the study finds that the programme does not reduce monetary poverty, as intended. In addition, the programme causes a significant decline in food expenditure. There is evidence that the underlying reason for the lack of impact is due to poor targeting. The findings point to the need to revamp the programme at both design and implementation stages.

Keywords: poverty, cash transfer, the state welfare card, Thailand

JEL: I32, I38

[1] This paper has benefited from comments and suggestions by Archawa Paweenawat, Riswandi, Nurina Merdikawati, and Christopher Cabuay. I thank Somchai Jitsuchon for insights into the state welfare program. I am also thankful to participants at the joint Brown Bag Seminar Series organized by Chulalongkorn University for their comments. I am grateful to Sathit Punsan for research assistance. I thank Karin Hosking for excellent copy editing. I thank the Puey Ungphakorn Institute for Economic Research (PIER) for financial support.

Cash subsidies for the poor: Evaluating Thailand’s welfare card scheme

1. Introduction

In October 2017, Thailand began implementation of a new social welfare programme, namely, “the state welfare card scheme”. This programme is considered the largest unconditional cash transfer in Thailand, with beneficiaries reaching over 20 per cent of Thailand’s population, and the objective of providing a monthly allowance to low-income earners. This program is commonly known as “the card for the poor” because it aims to provide a monthly allowance to low-income earners. Each month, the government transfers between 200 and 300 Baht to the beneficiary via an electronic card, with the exact figure depending on the annual income of the cardholder. In addition, the cardholders receive a discount of 45 Baht for cooking gas purchases every three months. They are also entitled to 500 Baht a month for train fares, 500 Baht for city bus and electric train fares, and 500 Baht for intercity bus fares.

Surprisingly, Thailand saw a substantial increase in the poverty rate in 2018, a year after implementing the large-scale unconditional cash transfer programme. The poverty rate rose from 7.87 percent in 2017 to 9.85 percent in 2018. The number of poor people in Thailand increased by more than 1.3 million in only a year. This is the fourth increase in poverty incidence in Thailand since 1988. A broad-based slowdown in economic growth is viewed as an underlying reason (Yang, Wang, and Dewina, 2020).

The purpose of this paper is to examine the poverty-reducing effect of this scheme focussing on monetary poverty.[2] Even though the academic literature on social protection programmes is extensive (Bastagli et al., 2019; Ladhani and Sitter, 2020; Millaán et al.,

[2] Monetary poverty is one of several dimensions of poverty. It measures the share of people with consumption of income level below the poverty line. While it does not capture every form of deprivation, it indicates individual’s ability to meet the basic needs (e.g., food, clothing, etc.) (Mahler et al., 2018; UNICEF, 2022).

2019), the extent to which Thailand's state welfare card scheme affects poverty incidence has not been examined. This paper therefore contributes to a broader literature on economic development and public policy by providing empirical evidence on the program impacts using a quasi-experimental method. It also informs the development policy debate on the role of economic growth and targeted programs in poverty reduction (Hanna and Olken, 2018; Pritchett and Lewis, 2022). Moreover, the analysis sheds light on the ongoing debate on unconditional cash transfer programs and other social protection programmes in response to the COVID-19 pandemic (World Bank, 2022).

Thailand is an excellent case study of the subject at hand because of the size of this recent unconditional cash transfer programme and the availability of data for empirical analysis. Thailand is an upper-middle-income country which has long been praised as a development success story. Over the past few decades, the country has seen a notable decrease in poverty, thanks to sustained economic growth (Warr, 2019). Increase in poverty incidence in 2018 deserves attention because it occurred during the period in which the Thai government initiated its state welfare card scheme.

This paper uses 'regression discontinuity methods' to identify the causal effects of the state welfare card programme on monetary poverty. As mentioned above, if an individual has an annual income of less than 100,000 Baht per year (a cutoff), they will get the state welfare card (treatment). This cutoff creates a discontinuity that forms the basis of regression discontinuity (Ozler, 2011). I find that the state welfare card scheme has no impact on total and consumption expenditure. As such, the findings do not support the claim that large-scale unconditional cash transfer programmes are associated with improvements in material well-being. Moreover, I find that this programme has a negative and significant impact on food expenditure, suggesting that individuals receiving transfers spend significantly more on other items. The findings are robust to several model assumptions. The lack of effect in Thailand makes the present study unique among the literature linking cash transfers to poverty reduction.

The findings of this study call for further research on the program. The absence of the program impact is possibly due to poor targeting. The number of beneficiaries of this state welfare programme in 2017 was over 12 million, a very high figure compared to the 5.8 million people who are considered poor by the official statistics from Thailand's National Economic and Social Development Council. Using the same dataset to provide suggestive evidence of poor targeting, I find that inclusion and exclusion errors exist. In the context of developing countries hit hard by the COVID-19 pandemic, this inclusion error is of more concern since these wasted resources could have been mobilised to those who were more vulnerable. Exclusion error is, however, difficult to examine and correct due to the large size of the informal sector.

The paper is structured as follows: Section 2 describes the analytical framework for the cash transfer-poverty reduction nexus. The next section provides some background information on Thailand's state welfare card programme. In Section 4, I show the methodology and discuss data. Section 5 reports the empirical results. The next section provides the robustness test for the main empirical results, and in Section 7, I discuss the results. A final section concludes.

2. The role of cash transfers in reducing poverty

The role of economic growth in reducing poverty has been extensively studied over the past few decades. A widely shared view in this literature is that, given an unchanged distribution of income, benefits of economic growth will distribute, though slowly, to other groups of people. This is the so-called "trickle-down effect" (Adams, 2004; Besley and Burgess, 2003; Chen and Ravallion, 2008; Kalwij and Verschoor, 2007). This is relevant for developing countries when such growth is associated with labour-intensive activities in which economic expansion leads to employment generation. This will result in an increase in income and, eventually, reduce poverty. Bhagwati (1988) named this “the pull-up effect”.

However, it has been held that economic growth alone may not eradicate poverty. This is partly because economic growth cannot be sustained for a sufficiently long period. If it is, such growth may be concentrated among the hands of a few, especially in the early stages of economic development. Marginalised people or those who work in the informal economy may have no connection to such spectacular economic expansion. As such, governments, in poor countries in particular, implement so-called complementary policies aimed at increasing living standards among those left behind in economic development. These complementary policies are also known as social protection programmes. Over the past century, these programmes have increased remarkably, especially in the era of employment injury, old-age pensions, and disability (International Labour Organization, 2021). Bastagli et al. (2016) explain that about 130 developing countries have at least one programme. Examples include Indonesia’s Program Kelaurga Herapan (PKH) and Mexico’s Oportunidades. Additionally, at least one social protection programme exists in every African country (Beegle, Honorati, and Monsalve, 2018).

Cash transfer programmes have become central in poverty reduction strategies among developing countries in recent decades. Over the same period, there has been a growing body of research examining the causal impacts of cash transfer programmes on a wide range of indicators, for instance, monetary poverty, education, health, and employment. A recent systematic literature review of 165 studies between 2000 and 2015 by Bastagli et al. (2019) suggests that cash transfer programmes mostly result in an increase in total expenditure and food expenditure, thus reducing so-called monetary poverty. A few studies have failed to find statistically significant effects of cash transfer programmes, largely due to programme features at design and implementation stages, such as low levels of transfers and changes in household behaviour.

Many developing countries also have adopted conditional cash transfer (CCT) programmes. These programmes have various objectives, including short-term poverty reduction through cash transfers and long-term poverty reduction through investment in human capital (Millán et al., 2019). PROGRESA, begun in Mexico in 1997, has become the role model for many CCT programmes. To be specific, it is a regular cash transfer, conditional on school enrolment and attendance for school-age children and regular visits to healthcare providers for young children. Several studies have investigated the short-term benefits of this programme (Behrman, Parker, and Todd, 2011; Levy and Schady, 2013; Parker and Todd, 2017). Schultz (2004) evaluated the Mexico Progresa programme using randomised assignment. It was found that the programme led to an average increase in enrolment of 3.4 percent of all students in grades 1 to 8. Using a Markov schooling transition model, Behrman, Sengupta, and Todd (2005) found that participation in the programme had several positive impacts on the education of children in Mexico, such as higher enrolment rates, less grade repetition and better grade progression, and lower dropout rates.

3. Thailand’s state welfare card programme

In 2017, the Thai government launched the state welfare card scheme, covering about 12 million people. A key feature of the programme is that its beneficiaries receive their payments through a cashless welfare card. Consistent with recent developments related to electronic transfer payment systems, the Thai government would like to know the poor not only by their names, but also to gather relevant information about how they spend their money to better formulate welfare programmes in the future. This section provides a brief account of the programme’s key features.

Since the introduction of the National e-Payment Master Plan in 2015, several types of payment infrastructure and electronic payment services now exist.[3] In 2016, the government initiated a project called "Registration for State Welfare". There were three criteria for eligibility: that participants be a Thai citizen; be at least 18 years old; and be unemployed or have annual income less than 100,000 Baht. Individuals whose annual income is less than 30,000 Baht are entitled to 3,000 Baht of cash assistance while those whose annual income is in the range of 30,000 to 100,00 Baht receive 1,500 Baht. Note that this is a one-off payment.

Following the 2016 scheme, the government began the state welfare card scheme in October 2017. These government welfare payments are made directly to recipients via state welfare cards. There are five criteria for eligibility: that they are a Thai citizen, are at least 18 years old, are unemployed or have an annual income in 2017 below 100,000 Baht, hold no financial assets worth more than 100,000 Baht, and do not own real estate.

The beneficiaries are not paid in cash, but via an electronic card worth 200 to 300 Baht. In the first year of the programme, the cardholders were required to use their card to buy goods at a registered store known as the "Thong Fah Shop". This shop sells everyday consumer products such as rice, shampoo, and other personal goods at subsidised rates. Additionally, the beneficiaries are entitled to 500 Baht per month for train fares, 500 Baht for city buses and electric trains, and 500 Baht for intercity bus fares.

Note that, from late 2018 until the current time, a few changes have been made to the use of the welfare card. Cardholders can save money on the card for the next month's spending, rather than being compelled to spend all the money in the one month. In addition, they can choose to top up the amount on their cards. Benefits for welfare cardholders also

[3] The National e-Payment Master Plan is a national strategy created by the Ministry of Finance and the Bank of Thailand, in cooperation with other government and private entities. The plan consists of five projects: the PromptPay project, the card usage expansion project, the e-Tax and e-Document systems project, the government e-Payment project, and the literacy and promotion project.

increase on an occasional basis. For example, eligible cardholders could sign up to receive an allowance for electricity and water bills for their households between October 2019 and September 2020.

Despite a large-scale monthly allowance being paid unconditionally to more than 12 million people, the number of poor people, measured by the national poverty line, increased by more than 1.3 million within one year. This is unusual for a country that has been painted as a showcase for poverty reduction. In this paper, I examine the impact of Thailand's state welfare card on monetary poverty.

4. Methodology

4.1 Data

To examine the causal impact of Thailand's state welfare card scheme on monetary poverty, I use data from the 2019 Socio-Economic Survey (SES), the nationally representative household survey conducted by the National Statistical Office (NSO) of Thailand. The number of households interviewed in this survey wave was 52,000. The survey provides detailed information on household income and expenditure and household characteristics, covering country-wide samples of private households both in municipal and non-municipal areas. Note that expenditure consists of transaction costs, including excise and sales taxes, of goods and services acquired during the interview period. Expenditure includes funds spent via the welfare card programme and other government assistance programmes.

There are 14 sections in the survey. Questions regarding welfare appear in Section 2. Since 2018, the survey has asked respondents about the state welfare card scheme ("Did you receive welfare from the state welfare card?"), allowing us to explore characteristics of those who are receiving benefits from the welfare card programme.

4.2 Identification

The hypothesise of the empirical analysis is that those who receive the state welfare card are more likely to have higher expenditure on both food and non-food items. This will in turn reduce monetary poverty, which is the goal of this welfare scheme.

However, those who receive the welfare card are not randomly assigned. This makes it difficult to examine the effectiveness of the scheme (the treatment effect) according to the formal theoretical foundation provided by the Rubin potential outcomes framework (Holland, 1986; Rubin, 1974). As such, a regression discontinuity (RD) method (Imbens and Lemieux, 2008; Lee and Lemieux, 2010) is used to address this methodological concern.

The first step is to set up a running variable and a cut-off. The running variable determines the cut-off. Then, the cut-off sorts the sample into two groups: treatment and control groups. As described by Lewis (2020), the idea behind the RD method is that, within narrow bounds on either side of the cut-off, observations are the same in all aspects, except for treatment assignment (the state welfare card). With this intuition, Cattaneo, Idrobo, and Titiunik (2020) state that regression discontinuity design is considered an effective method to reduce selection bias resulting from the non-random assignment of treatment.

I employ a sharp RD design with a single cut-off. A sharp RD design estimates the intent to treat (ITT) effects because they provide the impact of the policy as intended, assuming rules regarding the determination of the welfare cardholders have been followed. The cut-off is based on annual income equal to 100,000 Baht, which is a key criterion to receive the state welfare card.[4] Therefore, annual income is the running variable. To the right of the cut-off, an individual has annual income that is higher than the threshold. This group is

[4] To make it consistent with the criteria of the program, source of income is restricted to labour income. Individuals who have only capital income (e.g., income from stock holdings and rents) are excluded from the analysis.

known as “control”. To the left of the cut-off, an individual has annual income that is lower than the threshold. This group is called “treatment”.

Ideally, individual’s annual income in 2017 should be used as a running variable. However, since the survey is not repeated with the same household, it is not possible to track individual’s income received in 2017. This could bias the results from the RD method if there exists a significant change in the distribution of income between 2017 and 2019, especially among poor people. I assess this possibility by looking at the distribution of annual income in 2017 and 2019 and find that the distributions of income in these two years look similar (See Figure A1 in the appendix). In addition, the comparison of Lorenz curve for two years shows that the cumulative share of annual income from different sections of the sample are close, especially among the low-income earners (See Figure A2 in the appendix). This indicates that there is no significant change in the distribution of income between 2017 and 2019.

For identification, assume that there are n households that $i = 1,2,3 \dots, n$. Each household has a running variable X_i. X_0 is the known cut-off. Households with $X_i<X_0$ are assigned to treatment and households with $X_i \geq X_0$ are assigned to control. Treatment is designated by $T = 1$ while control is $T = 0$.

Each household i has two potential outcomes: $Y_i(0)$ and $Y_i(1)$. $Y_i(0)$ is the outcome to the right of the cut-off (control) and $Y_i(1)$ is the outcome to the left of the cut-off (treatment). As such, $Y_i(1) - Y_i(0)$ is the causal impact of the state welfare card. However, either $Y_i(0)$ or $Y_i(1)$ can be observed at the mean time. As described by Imbens and Lemieux (2008) and Lewis (2020), average effects across subgroups of the relevant population are of interest, and this underlies the regression discontinuity design.

Let $T_i = 0$ if a household is in the control group and $T_i = 1$ is a household is in the control group. The observed outcome is:

$$Y_i = \begin{cases} Y_i(0) \text{ if } T_i = 0 \\ Y_i(1) \text{ if } T_i = 1 \end{cases} \tag{1}$$

Given the cut-off, the observed average outcome can be written as follows.

$$E[Y_i|X_i] = \begin{cases} E[Y_i^0|X_i] \text{ if } T_i = 0 \\ E[Y_i^1|X_i] \text{ if } T_i = 1 \end{cases} \tag{2}$$

where $E[Y_i^0|X_i]$ and $E[Y_i^1|X_i]$ are regression functions. The average causal effect of the state welfare card, τ, at the cut-off, $c = 0$, is:

$$\tau = E[Y_i(1) - Y_i(0)|X_i = c] = E[Y_i(1)|X_i = c] - E[Y_i(0)|X_i = c] \tag{3}$$

The key identifying assumption is that potential outcomes – that is, $[Y_i^0|X_i]$ and $E[Y_i^1|X_i]$ – are continuous at X_0 at the cut-off. As explained in Cattaneo, Idrobo and Titiunik (2020), this assumption is important since it implies that outcomes (Y_i) just to the right of the cut-off (control) can been seen as valid counterfactuals for outcomes just to the left of the cut-off (treatment). In addition, since there is no overlap or common support, we rely on minimal extrapolation based on the continuity assumption. This means that units with different values of the running variable are compared (Cunningham, 2021).

The RD estimation equation can be written as:

$$Y_i = \tau T_i + g(X_i) + \mu_i \tag{4}$$

where τ is the treatment effect, $g(X_i)$ is a polynomial function of unspecified degree, and μ_i is the error term. The treatment effect is estimated using non-parametric local polynomial regressions within narrow bandwidths on each side of the cut-off. The regression is estimated using polynomials of degree one and two. A triangular kernel is used while bandwidths are fixed using data-driven techniques to minimise the mean squared error of the estimated treatment effects. The estimated treatment effects are intent-to-treat (ITT) effects because they provide the impact of the policy as intended.

5. Empirical results

This section starts with the results from the running variable manipulation test. The validity of RD methods requires that it be free of manipulation. This means that annual income for some people does not systematically change from their true value to influence treatment assignment. Manipulation can occur if welfare cardholders have knowledge about the cut-off and have incentives and ability to change the score so that they can be assigned to the treatment group. In the case of the state welfare card, the cut-off (eligibility for welfare) is proposed by the government based on the official poverty line, so manipulation in this case seems unlikely.

Figure 1 shows the density distribution of the running variable (annual income). It suggests that there is no obvious discontinuity in density around the cut-off. A formal test of the null hypothesis that there is no discontinuity is shown in Table 1. The purpose of this test is to examine whether there is evidence of discontinuity in the density of annual income at the cut-off. Presence of discontinuity provides evidence of self-selection or non-random sorting of individuals into control and treatment groups (Cattaneo, Jansson, and Ma, 2018). Table 1 shows both conventional (a conventional Wald test without bias correction) and robust (robust bias-correction) versions of the test. The results cannot reject the null hypothesis of no manipulation.

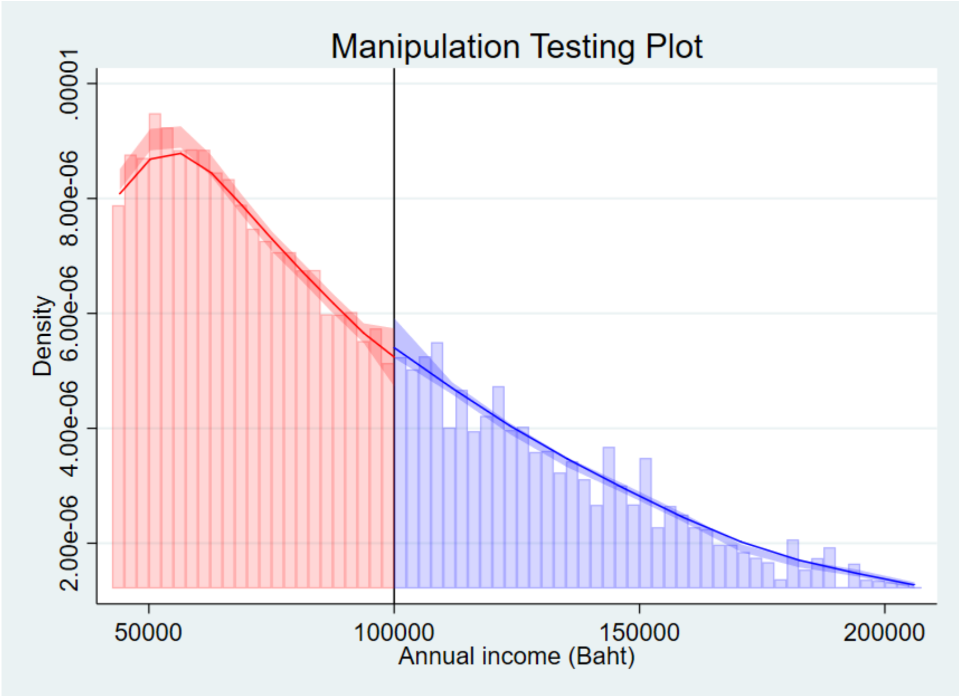

Figure 1: Density of annual income

Notes: The cut-off for determining the welfare cardholder is 100,000 Baht. The width of the bin is 2,500 Baht.

Table 1: Results from running variable manipulation test

RD manipulation test method	Number of obs.	61,758	
	Model	Unrestricted	
	BW method	each	
	Kernel	Triangular	
	VCE method	Jackknife	
The cut-off		Left of the cut-off	Right of the cut-off
	Number of obs.	34,745	27,013
	Effective Number of obs.	6,804	9,499
	Order est. (p)	2	2
	Order bias (q)	3	3
	BW est. (h)	18,641.08	35,353.11
Hypothesis testing	Method	T	P-value
	Conventional	0.8036	0.4216
	Robust	1.0642	0.2872

Figure 2 shows the standard regression discontinuity plot using a polynomial of degree two. The dots in the plot are named bins. The bins indicate average values of annual income over certain ranges. Plots are drawn using a uniform kernel. There are four outcome variables: total expenditure (Panel A), consumption expenditure (Panel B), food expenditure (Panel C), and tobacco and alcoholic beverages expenditure (Panel D). As the figure shows, there is no obvious jump around the cut-off, except in Panel C. This implies that the state welfare card may fail to increase expenditure on necessary items which are central to the material well-being of the cardholder. As shown in Panel C of Figure 2, there is a pronounced drop in expenditure on food at the cut-off. I cautiously conclude that the welfare card programme may have caused a decline in food expenditure. The plot is only indicative, however. I continue the analysis by employing a formal estimation of treatment effects by estimating Equation (4).

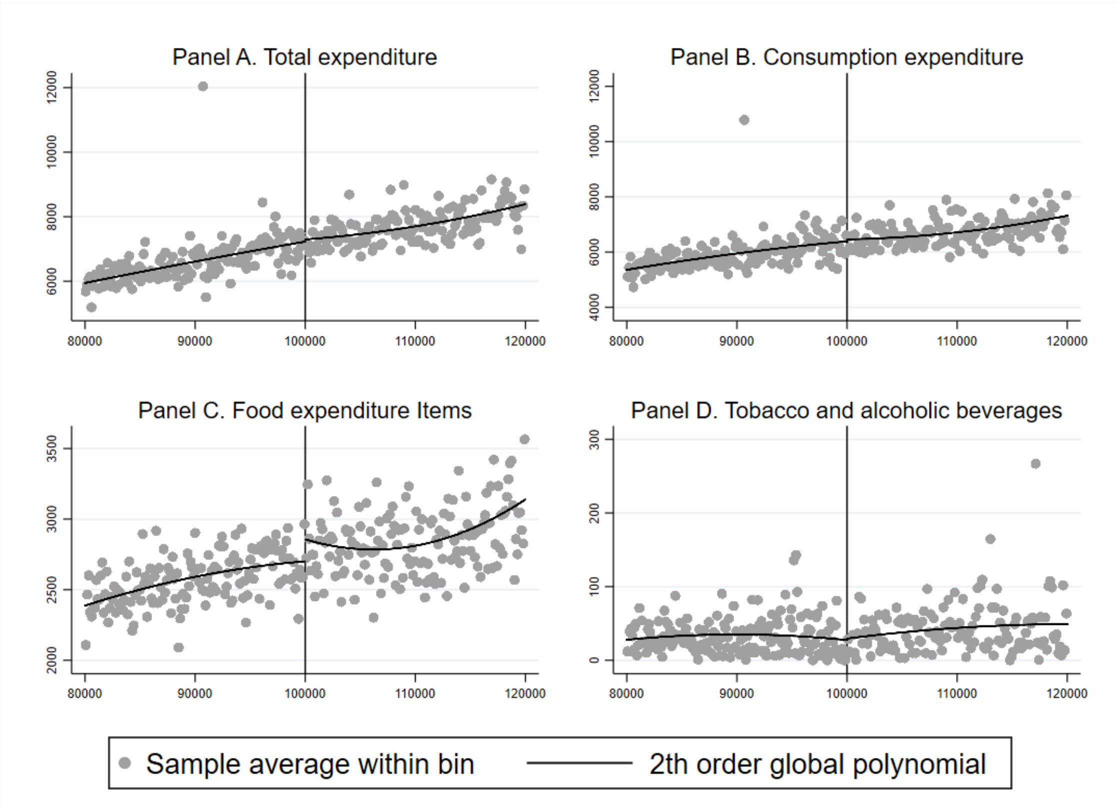

Figure 2: RD plot

As previously mentioned, Equation (3) is estimated to examine the state welfare card treatment effects using non-parametric estimation techniques, a triangular kernel, and MSE-optimal bandwidths. The impacts are estimated using polynomials of degree one and two. Table 1 reports bandwidth around the cut-off, the effective observations to the left and right of the cut-off, the conventional treatment effect, and robust p values and confidence intervals.

As shown in Table 2, none of the estimated treatment effects is statistically significant at the 5% level, except the impact on food expenditure. Using a polynomial degree one, the programme causes a 29-Baht increase in total expenditure per capita. The second-degree polynomial regression result yields a negative but not significant effect, suggesting that the programme results in a 28-Baht decrease in total expenditure per capita. However, neither estimated treatment effect is statistically significant at the 5% level. I conclude that the welfare card programme did not have the intended impact on total expenditure.

Table 2: Effects of the state welfare card on expenditure

	Degree of polynomials	**Bandwidth**	**Obs. left**	**Obs. Right**	**τ**	**p**	**95% CI**	
Total expenditure	1	27,040.11	10,466	7,726	29.37	0.93	-190.55	174.30
	2	32,682.46	13,168	8,964	-28.44	0.65	-182.11	291.20
Consumption expenditure	1	24,672.87	9,426	7,104	53.11	0.79	-204.89	155.69
	2	32,487.31	13,048	8,923	-6.16	0.78	-195.18	261.44
Food	1	27,987.40	10,901	7,929	-26.34	0.31	-32.62	103.97
	2	30,019.76	11,868	8,369	-90.12	0.03	12.37	195.25
Tobacco and Alcohol	1	29,320.97	11,539	8,238	-0.42	0.87	-8.69	7.31
	2	37,817.09	15,835	10,010	1.37	0.59	-11.92	6.76

Notes: There are four dependent variables: total expenditure per capita, consumption expenditure per capita, food expenditure per capita, and tobacco and alcoholic beverages per capita. A data-driven RDD bandwidth selection is employed. Total observations are 61,826. Obs Left and Obs Right are the effective numbers of observations used in the analysis. τ is the conventional estimated treatment effect. P-value and 95% confidence interval are robust.

Moreover, the estimated treatment effects from the first- and second-degree polynomial regression on consumption expenditure are small and positive but not statistically significant at the 5% level. Therefore, the welfare card programme does not have the intended impact on consumption expenditure, as suggested by the RD plot.

In addition, the first-degree polynomial regression output shows a negative but not statistically significant treatment effect on food expenditure. The finding indicates that the state welfare programme causes a 26-Baht decrease in per capita expenditure on food. However, the estimated treatment effect from the second-degree polynomial regression is negative and statistically significant impact at the 5% level. To be specific, the state welfare card results in a decrease in food expenditure per capita by 90 Baht. These results are consistent with the RD plot. Therefore, there is evidence suggesting that individuals receiving the transfers spend less on food.

Lastly, the estimated treatment effects on expenditure on tobacco and alcoholic beverages are not statistically significant at the 5% level. The result from the first-polynomial regression shows a small negative impact of the state welfare card on per capita expenditure on tobacco and alcoholic beverages. The programme causes a 0.4-Baht fall in expenditure on tobacco and alcoholic beverages. The treatment effect is positive but still not statistically significant at the 5% level when estimating the model using the second-polynomial regression.

Overall, the results suggest that the welfare card programme has failed to increase expenditure per capita as was intended to do.

6. Robustness tests

This section provides a set of robustness tests: alternative cut-off, placebo thresholds, and covariate balance.

6.1 Alternative cut-off

As explained earlier, those who earn a maximum of 30,00 Baht a year will receive 300 Baht per month. Broadly speaking, this threshold is based on the official poverty line. Therefore, the effects of the state welfare card may be more pronounced among those who are extremely poor. I examine this possibility by re-estimating Equation (4) using a new cut-off. The cut-off is 30,000. To the right of the cut-off, an individual's annual income is greater than the cut-off (control) and to the left of the cut-off, an individual's annual income is less than the cut-off (treatment).

The standard RD plot drawn using a uniform kernel with polynomial of degree two is shown in Figure 3. As the figure shows, there is no pronounced jump in each type of expenditure at the cut-off. This suggests that the state welfare card may have no impact on various types of expenditure. A formal estimation of the treatment effect is reported in Table 3.

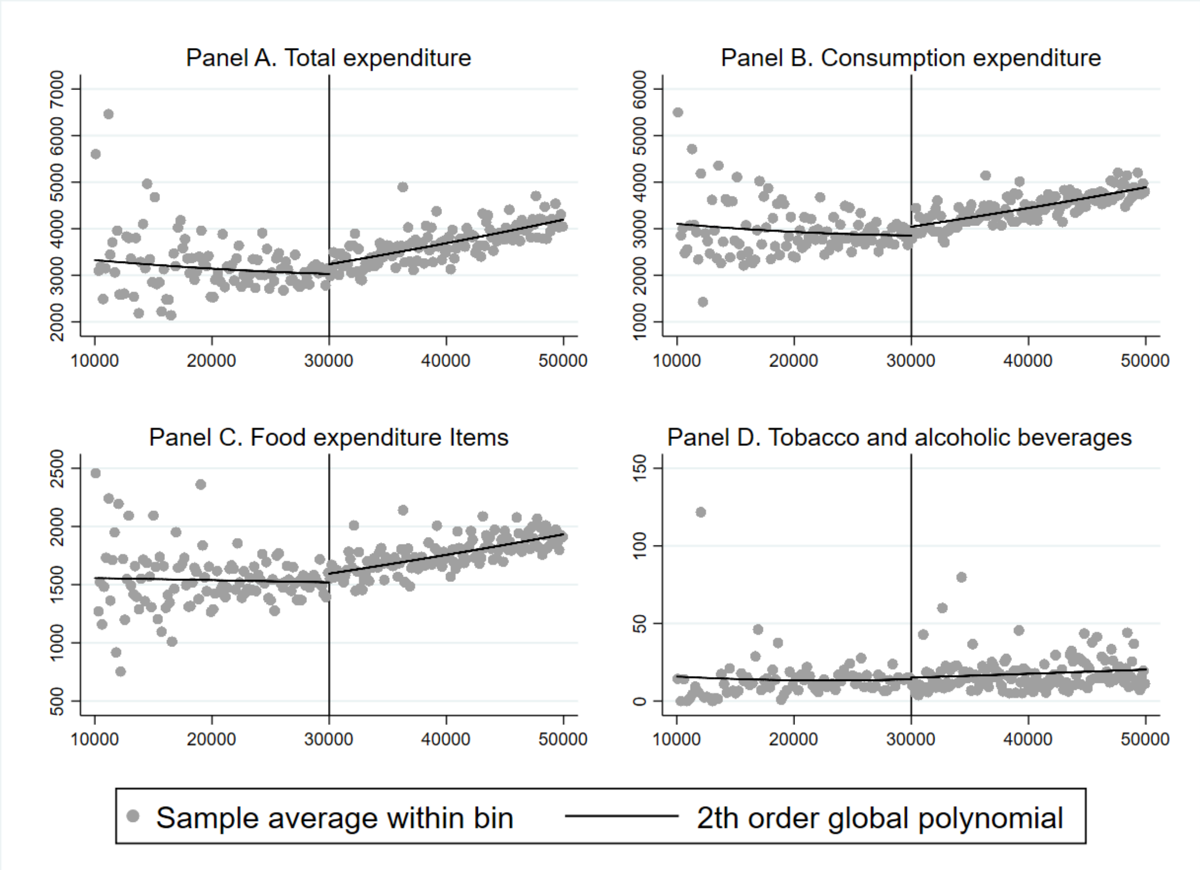

Figure 3: RD plot using per capita expenditure being 30,000 Baht as the cut-off

Table 3: Effects of the state welfare card on expenditure using alternative cut-off

	Degree of polynomials	Bandwidth	Obs. Left	Obs. Right	τ	p	95% CI	
Total expenditure	1	8,436.27	1,935	3,394	182.97	0.14	-53.20	383.10
	2	11,336.92	2,314	4,724	-168.58	0.26	-112.91	419.73
Consumption expenditure	1	8,850.68	1,994	3,564	-170.01	0.13	-44.37	359.35
	2	11,670.15	2,354	4,894	-162.77	0.22	-94.38	409.02
Food	1	9,295.24	2,055	3,785	-87.42	0.02	14.29	170.98
	2	11,937.11	2,378	5,024	-77.66	0.15	-25.28	167.23
Tobacco and Alcohol	1	8,338.50	1,917	3,349	1.58	0.37	-8.73	3.28
	2	10,365.99	2,192	4,261	4.57	0.12	-13.03	1.41

Notes: The cut-off is annual income being 30,000 Baht. There are four dependent variables: total expenditure per capita, consumption expenditure per capita, food expenditure per capita, and tobacco and alcoholic beverages per capita. A data-driven RDD bandwidth selection is employed. Total observations are 61,826. Obs Left and Obs Right are the effective numbers of observations used in the analysis. τ is the conventional estimated treatment effect. P-value and 95% confidence interval are robust.

As shown in Table 3, most of the estimated treatment effects are not statistically significant at the 5% level. The exception is expenditure on food. The result for the non-parametric regression using a polynomial of degree one suggests that the state welfare card causes an 87-Baht decrease in food expenditure. The estimated treatment effect is statistically significant at the 5% level. The estimated treatment effect is negative but not statistically significant at the 5% level when estimating the model using a polynomial of degree two. I tentatively conclude that the state welfare card programme does not have its intended effect on consumption expenditure.

6.2 Placebo cut-off

In the RD method, we should not see significant treatment effects at fake cut-off. I test whether the estimated treatment effects at the actual cut-off are spurious by examining the impact at placebo cut-off. Equation (3) is estimated using the fake cut-off at 200,000, non-parametric estimation techniques, a triangular kernel, MSE-optimal bandwidths, and polynomials of degree one. Table 4 shows the results. I find that none of the alternative cut-offs provide statistically significant results except expenditure on tobacco and alcoholic beverages. Note however that expenditure on tobacco and alcoholic beverages is not the intended impact of the state welfare card. The extent to which the programme causes an increase in spending on these items should be further explored.

Table 4: Effects of the state welfare card on expenditure using placebo cut-off

	Bandwidth	**Obs. Left**	**Obs. Right**	τ	p	**95% CI**	
Total expenditure	36,069.65	7,994	4,690	88.87	0.396	-390.06	154.32
Consumption expenditure	50,534.22	6,083	3,096	110.34	0.563	-540.73	294.44
Food expenditure	59,841.42	7,824	3,478	-45.86	0.468	-108.9	237.07
Tobacco and alcohol	54,808.48	6,843	3,283	-14.11	0.044	0.47	32.97

Notes: The cut-off is annual income being 200,000. A data-driven RDD bandwidth selection is employed. Total observations are 61,826. Obs Left and Obs Right are the effective numbers of observations used in the analysis. τ is the conventional estimated treatment effect. P-value and 95% confidence interval are robust.

6.3 Covariance balance

The RD method assumes that individuals are essentially the same on either side of the cut-off. This means that other potential determinants of the outcome variables (a set of expenditure categories) are balanced around the cut-off. If not, those variables may confound the estimated treatment effects. The usual covariate balance test is employed to partially test this assumption. It is found that the covariates are well balanced across treatment and control groups. Therefore, none of the covariates, for which data exist, confound the estimated treatment effects.

7. Discussion

The state welfare card scheme launched in 2017 did not have the intended impact on total and food expenditure among low-income earners. There are two key issues.

First, despite mild economic growth and a monthly allowance being paid to more than 12 million people across the country, the number of poor people increased from 5.32 million in 2017 to 6.68 million in 2018. Over the same period, the poverty rate increased by about 2 percentage points based on national estimates. While there could be many factors at play, such as broad-based slowdowns in economic growth and low wage growth as argued by Yang, Wang, and Dewina (2020), the role of the welfare card programme intended to help low-income and vulnerable households has been insufficiently studied.

Why did the state welfare card programme fail to increase consumption expenditure as intended? I argue that high inclusion and exclusion errors for targeted programme in the design stage played a key role. Inclusion errors (also called leakage) exist when programme reach unintended beneficiaries, while exclusion errors (also called undercoverage) exist when programme fail to reach intended beneficiaries. Inclusion error wastes resources while exclusion error makes the programme ineffective.

I evaluate these errors by looking at annual income among those who receive and do not receive the state welfare card. The analysis is based on the socio-economic survey conducted in 2019 to understand those who received the welfare card. Ideally, calculation would be much more precise if I could get economic and demographic profiles of the beneficiaries of the programme. The data I have only allow me to examine these errors from a nationally representative sample of 61,826 people. Table 5 shows the results.

Table 5: State welfare cardholders by income level

	Annual income less than 100,000 Baht	Annual income greater than 100,000 Baht	Total
Not receive a welfare card	27,591 (52.03) [79.40]	25,440 (47.97) [93.95]	53,031 (100.00) [85.77]
Receive a welfare card	7,157 (81.38) [20.60]	1,638 (18.62) [6.05]	8,795 (100.00) [14.23]
Total	34,748 (56.20) [100.00]	27,078 (43.80) [100.00]	61,826 (100.00) [100.00]

Notes: Figures in parentheses refer to percentage to row totals and those in square brackets refer percentages to column totals.

It is found that inclusion error exists, but it is not very high. As shown in Table 5, of 8,795 people who receive the state welfare card, 19 percent have annual income greater than 100,000 Baht (who should not have been receiving the welfare card). In addition, there are substantial gaps in living standards among those who receive the welfare card. As shown in Table A1 in the Appendix, among those who receive the card, monthly consumption expenditure is on average twice as high among individuals who have annual income more than 100,000 Baht as among poorer counterparts.

Exclusion error is high, however. 80 percent of those who have annual income less than 100,000 Baht are not reached by the state welfare card. This indicates that, for some reason, those who are the same in terms of economic disadvantage have different access to the welfare programme intended to reach them.

Table 6 shows the distribution of the welfare cardholders between poor and non-poor people. It suggests that exclusion and inclusion errors are substantial. For inclusion error, it is found that about 85 percent of the welfare cardholders are not poor. For exclusion error, about 75 percent of the poor do not receive the welfare card. Despite the limitation of the data used to perform an analysis on inclusion and exclusion error, there exists a significant amount of poor people who do not have access to this welfare program.

Table 6: State Welfare cardholders by poverty profile

	Poor	**non-poor**	**Total**
Not receive a welfare card	3,719 (7.01) [73.40]	49,312 (92.99) [86.88]	53,031 (100) [85.77]
Receive a welfare card	1,348 (15.33) [26.60]	7,447 (84.67) [13.12]	8,795 (100) [14.23]
Total	5,067 (8.20) [100]	56,759 (91.80) [100]	61,826 (100) [100]

Notes: Figures in parentheses refer to percentage to row totals and those in square brackets refer percentages to column totals, individual is classified as poor if his or her monthly consumption per capita is lower than the official poverty line (2,987 baht for those who live in municipal area and 2,499 for those in non-municipal area)

The problem of inclusion error is not surprising. This is regarded as targeting inefficiency. The eligibility criteria for the state welfare card scheme are based on individuals. It is therefore possible that an applicant may be eligible for assistance despite sharing a house with other family members who are not low-income earners and do not need state financial aid. In 2020, the family-based income qualification was one of the criteria for the new round of registration. Total earnings of family members must not be greater than 200,000 Baht per year. This revision aims to target low-income earners.

The next question is why exclusion error is high. This error is regarded as coverage inefficiency. The state welfare programme has several selection criteria such as age, annual income, financial assets, and real estate ownership. As such, it is possible that when these criteria are considered, some people who have annual income less than 100,000 Baht per year or are classified as poor by the poverty line become ineligible for the state welfare card. Large exclusion errors manifest failure to screen the poor before initiating the programme.

Why does the current registration process make it difficult to find the poor? As mentioned above, in 2016 the government implemented a project to compile a list of low-income earners. This is a self-registration process since qualified persons, or those who think they are poor enough to receive the welfare, are asked to provide information on the status of their income, assets, and debts. As explained by Jitsuchon, Chamornchan, and Amornrat (2017), Thailand has a particularly large informal sector, making it difficult to track the incomes of the poor working in the informal sector. Self-registration therefore casts doubt on the ability to find the poor. They also called for combing several datasets on vulnerable people, for example, the disabled and elderly without caregivers, to better identify the poor. Unfortunately, the government is yet to revise the registration process.

Second, the failure to find treatment effects may possibly be due to implementation features of the state welfare programme, including misuse of the card at the Thong Fah Shop and low levels of transfers. During the period studied, cardholders were required to use their cards to buy goods at the Thong Fah Shop. Cardholders may have sold their cards to stores in exchange for money at lower prices. This unintentionally creates a win-win situation for the state welfare cardholders and the shop owners. The welfare intended to help the poor may leak to elsewhere. More research would be needed to confirm whether confiscation of the card occurs widely, precluding welfare cardholders from receiving the benefits of the programme as intended. However, one may think that state welfare cardholders could use their money to buy unnecessary items such as alcoholic beverages and tobacco, which are not sold at the Thong Fah Shop. Evidence from the RD estimate does not support this claim.

8. Conclusions

This paper has examined the effectiveness of the state welfare card scheme launched by the government of Thailand in 2017. The findings suggest that the scheme had no intended effect on monetary poverty. To be specific, the estimated treatment effect on consumption expenditure is not statistically significant. In addition, the estimated treatment effects of the programme on food expenditure are negative and statistically significant, suggesting that individuals receiving transfers spend less on food. The policy also had no effect on those who were poorer and receiving higher amounts of cash handouts.

The findings are robust to alternative model specifications and assumptions. Given a large evidence base showing the poverty-reducing effects of cash transfers in several developing countries, the null effect here thus deserves attention from both policymakers and scholars to undertake further research. There is evidence of high inclusion and exclusion errors and argue that they could be underlying reasons behind the lack of effects. The study helps point out the need to revamp the programme at both design and implementation stages.

Future research should explore inclusion and exclusion error in more details. In terms of methodology, the treatment effect could explore the treatment-on-the-treated (TOT) effects using the Fuzzy RD method. TOT effects yield the impacts of treatment on those who have received treatment (the state welfare card) relative to those who were only intended to be treated by the welfare. This is because it is possible that individuals assigned to the treatment group would have not received the welfare card. For example, if people own assets worth more than 100,000 Baht, they will not be eligible for the welfare. In this case, people classified as treated will not have been treated. It is also possible that individuals assigned to the control group may have received the welfare, for example, if they were unemployed. As such, people classified as control would have received the welfare card. Unfortunately, the data I have do not allow me to investigate the treatment impacts using this model specification. In addition, since there was a significant and negative impact on food expenditure, future research could shed light on unintended consequences on children's weight and height among beneficiaries of the programme.

References

Adams, R. (2004). Economic growth, inequality and poverty: Estimating the growth elasticity of poverty. *World Development, 32*(12), 1989-2014.

Bastagli, F., Hagen-Zanker, J., Harman, L., Barca, V., Sturge, G., & Schmidt, T. (2019). The impact of cash transfers: A review of the evidence from low- and middle-income countries. *Journal of Social Policy, 48*(3), 569-594.

Bastagli, F., Hagen-Zanker, J., Harman, L., Barca, V., Sturge, G., and Schmidt, T. (2016). Cash transfers: What does the evidence say? A rigorous review of programme impact and of the role of design and implementation features. London: Overseas Development Institute. Retrieved from https://odi.org/en/publications/cash-transfers-what-does-the-evidence-say-a-rigorous-review-of-impacts-and-the-role-of-design-and-implementation-features/

Beegle, K., Honorati, M., & Monsalve, E. (2018). Reaching the poor and vulnerable in Africa through social safety nets. In: Beegle, K., Coudouel, A., & Monsalve, E. (Eds.), *Realizing the full potential of social safety nets in Africa* (pp. 49-86). Washington, DC: World Bank.

Behrman, J., Sengupta, P., & Todd, P. (2005). Progressing through PROGRESA: An impact assessment of a school subsidy experiment in rural Mexico. *Economic Development and Cultural Change, 54*(1), 237-275.

Behrman, J. R., Parker, S. W., & Todd, P. E. (2011). Do conditional cash transfers for schooling generate lasting benefits? A five-year followup of PROGRESA/Oportunidades. *Journal of Human Resources, 46*(1), 93-122.

Besley, T., & Burgess, R. (2003). Halving global poverty. *Journal of Economic Perspectives, 17*(3), 3-22.

Bhagwati, J. N. (1988). Poverty and public policy. *World Development, 16*(5), 539-555.

Cattaneo, M. D., Jansson, M., and Ma, X. (2018). Manipulation testing based on density discontinuity. *Stata Journal*, 18(1), 234-261.

Cattaneo, M. D., Idrobo, N., and Titiunik, R. (2020). *A practical introduction to regression discontinuity designs: Volume I.* Elements in Quantitative and Computational Methods for Social Science. Cambridge: Cambridge University Press.

Chen, S., & Ravallion, M. (2008). The developing world is poorer than we thought, but no less successful in the fight against poverty. *Quarterly Journal of Economics, 125*(4), 1577-1625.

Cunningham, S. (2021). Causal inference: The Mixtape. London: Yale University Press.

Hanna, R., & Olken. (2018). Universal basic incomes versus targeted transfers: Anti-poverty programs in developing coutries. *Journal of Economic Perspectives*, 32(4), 201-206.

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association, 81*(396), 945-960.

Imbens, G., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics, 142*(2), 615-635.

International Labour Organization. (2021). *World social protection report 2020-22: Social protection at the crossroads – in pursuit of better future.* Geneva: International Labour Organization. Retrieved from https://www.ilo.org/global/publications/books/WCMS_817572/lang--en/index.htm

Jitsuchon, S., Chamornchan, P., & Amornrat, K. (2017). *Registering the poor to beat poverty.* Bangkok: Thailand Development Research Institute. Retrieved from https://tdri.or.th/en/2017/02/registering-the-poor-to-beat-poverty/

Kalwij, A., & Verschoor, A. (2007). Not by growth alone: The role of distribution of income in regional diversity in poverty reduction. *European Economic Review, 51*(4), 805-829.

Ladhani, S., & Sitter, K. C. (2020). Conditional cash transfers: A critical review. *Development Policy Review, 38*(1), 28-41.

Lee, D. S., & Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature, 48*(2), 281-355.

Levy, S., & Schady, N. (2013). Latin America's social policy challenge: Education, social insurance, redistribution. *Journal of Economic Perspectives, 27*(2), 193-218.

Lewis, B. D. (2020). How do mayors get elected? The causal effects of pre-electoral coalitions on mayoral election outcomes in Indonesia. *Local Government Studies, 46*(3), 394-413.

Mahler, D. G., Friedman, J., Lugo, M. A., & Sharma, D. (2018). Does monetary poverty capture all aspects of poverty? Retrieved from https://blogs.worldbank.org/developmenttalk/does-monetary-poverty-capture-all-aspects-poverty

Millán, T. M., Barham, T., Macours, K., Maluccio, J. A., & Stampini, M. (2019). Long-term impacts of conditional cash transfers: Review of the evidence. *World Bank Research Observer, 34*(1), 119-159.

Ozler, B. (2011). Evaluating a large cash transfer program? Don't ignore Regression Discontinuity Design. Retrieved from https://blogs.worldbank.org/impactevaluations/evaluating-a-large-cash-transfer-program-don-t-ignore-regression-discontinuity-design

Parker, S. W., & Todd, P. E. (2017). Conditional cash transfers: The case of Progresa/Oportunidades. *Journal of Economic Literature, 55*(33), 866-915.

Pritchett, L., & Lewis, A. (2022). Economic growth is enough and only economic growth is enough. Retrieved from https://lantpritchett.org/wp-content/uploads/2022/05/Basics-legatum-paper_short.pdf

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology, 66*(5), 688.

Schultz, P. T. (2004). School subsidies for the poor: Evaluating the Mexican Progresa poverty program. *Journal of Development Economics, 74*(1), 199-250.

UNICEF. (2022). A practical guide to monetary poverty analysis: Informing policies and programmes to address child poverty. New York: UNICEF. Retrieved from https://www.unicef.org/media/117736/file/Monetary%20child%20poverty%20analysis%20policies.pdf

Warr, P.G. (2019). Economic development of post-war Thailand. In: Chachavalpongpun, P. (Ed.), *Routledge Handbook of Contemporary Thailand* (pp. 36-52). New York: Routledge.

World Bank. (2022). World Development Report 2022. Washington, DC: World Bank.

Yang, J., Wang, S., & Dewina, R. (2020). *Taking the pulse of poverty and inequality in Thailand.* Washington, DC: World Bank Group. Retrieved from https://www.worldbank.org/en/country/thailand/publication/taking-the-pulse-of-poverty-and-inequality-in-thailand

Appendix

Figure 1: Distributions of annual income in 2017 and 2019

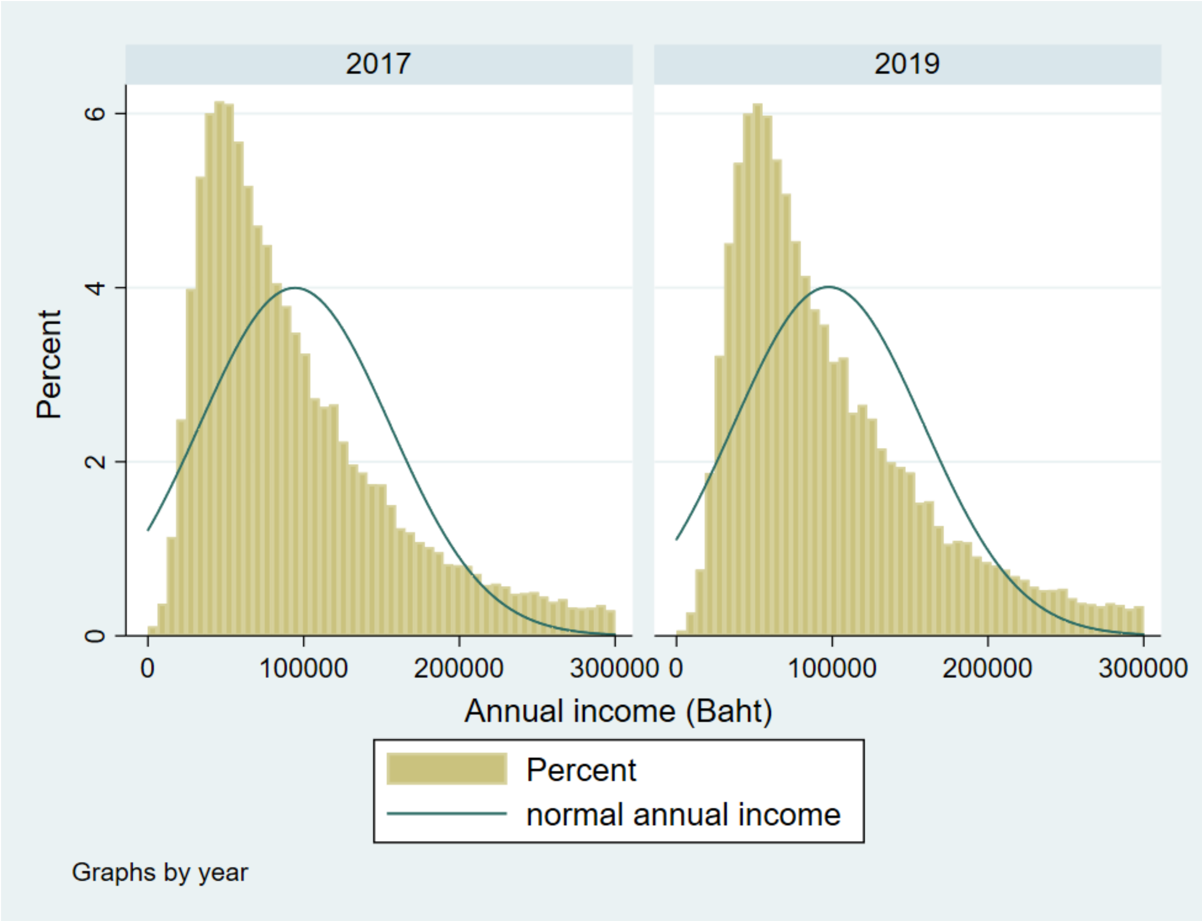

Figure A2: A comparison of Lorenz curves for 2017 and 2019

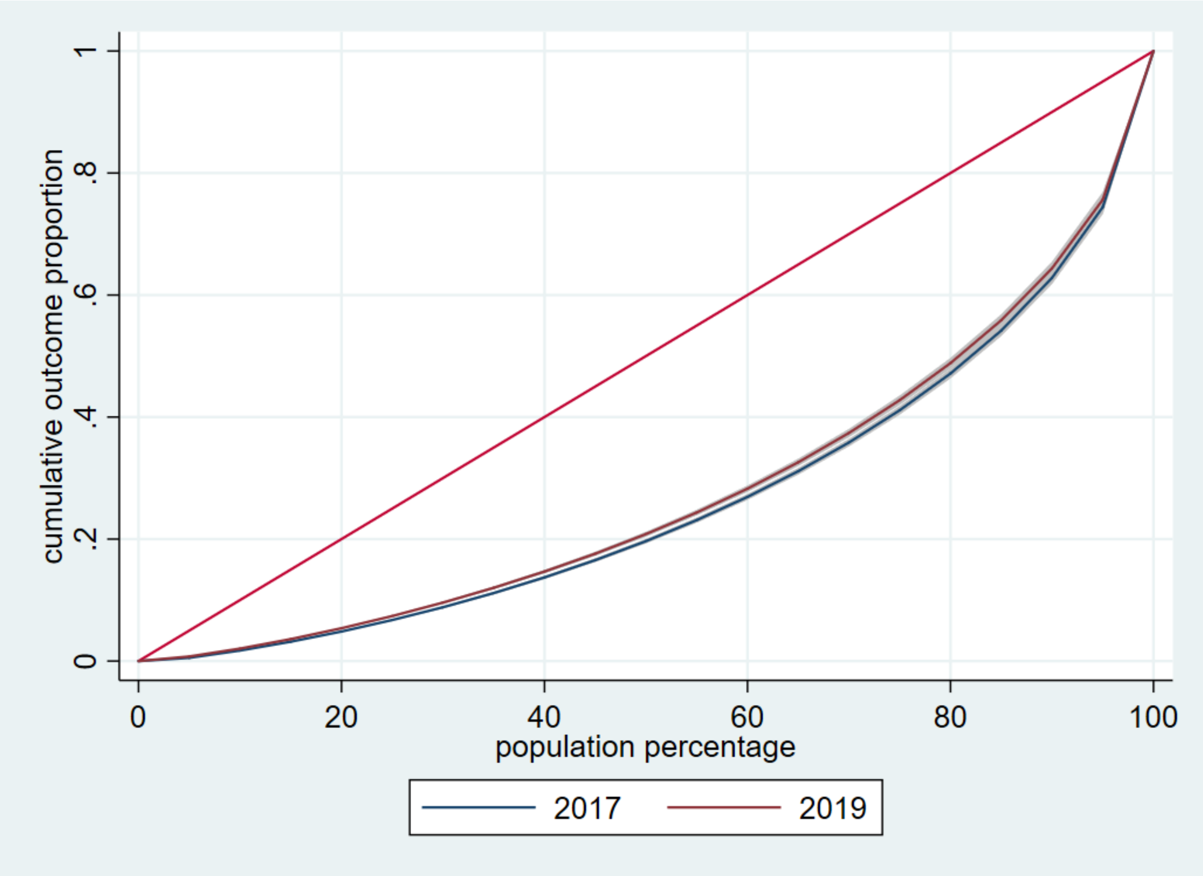

Table 1A: Monthly per capita consumption expenditure among households

	Annual income less than 100,000 Baht	Annual income greater than 100,000 Baht	Total
Not receive a welfare card	4,564.25 (2,189.05)	10,619.88 (6,680.56)	7,469.25 (5,749.37)
Receive a welfare card	3,986.51 (1,151.27)	7,390.14 (3,290.53)	4,620.41 (2,393.68)
Total	4,445.25 (2,086.89)	10,424.50 (6,570.96)	7,063.99 (5,491.65)

Notes: Standard deviation in parentheses.