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Digital Payment, Household Consumption Behavior, and Financial Literacy

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Abstract

This study examines the impact of innovations in the payment system on household finance, focusing on consumption behaviors and financial literacy among low-income households. The investigation utilizes Thailand's introduction of the cashless State Welfare Card to low-income households in 2017 as a quasi-experiment setting. The primary data sources for this study include the large-scale country-wide household socioeconomic survey (SES) conducted by Thailand's National Statistical Office (NSO) and survey data from individuals in four provinces of Thailand. The empirical strategy in this study is primarily fuzzy regression discontinuity design.

The results of the study reveal that individuals who receive the cashless State Welfare Card experience effective increases in consumption of the food and beverage items that are the target of the policy. Contrary to concerns about adverse impacts, such as overconsumption or using the card for unintended items like cigarettes, there is no evidence supporting these claims. Instead, people using the state welfare card exhibit better financial literacy and reduced risk-taking consumption behavior. The result underscores the importance of financial literacy training provided alongside the card. However, the study does not find sufficient evidence to suggest a significant impact on trust in the financial system.

Keywords— Household Finance, Financial Technology, State Welfare Card, Fuzzy Regression Discontinuity Design

1 Introduction

According to Amstad et al. (2019), Fintech, or financial technology, is broadly defined as advanced technology that improves and automates the delivery and use of financial services to consumers and businesses. Examples include payment services and market infrastructure (such as mobile phone wallets, crypto assets, and remittance services), investment management (internet banking, online brokers, robo-advisors, personal financial management tools), and alternative finances (crowdfunding, peer-to-peer lending, internet-only banks), leveraging transaction data and others for credit appraisals.

Fintech has witnessed significant international development in the past decade. Specifically, Asia has made rapid progress in every aspect of fintech. In Africa, the increasing use of mobile money has enhanced financial service accessibility for the unbanked. The fintech industry is also growing in Europe, though not evenly distributed. However, regions like the Middle East and Central Asia are still in the early stages of fintech development. A major contributing factor is government support, aiming to enhance economic efficiency and financial inclusion through fintech.

Fintech development can bring more opportunities to different household segments: the banked, the underbanked, and the unbanked, especially in less developed countries. Globally, the Group of Twenty (G20) established high-level principles on digital financial inclusion in 2016, while the International Monetary Fund (IMF) and the World Bank co-developed the Bali Fintech Agenda in 2018, addressing critical issues for policymakers. However, it is essential to note that more than government support is needed to guarantee the success of fintech development, as technology adoption takes time and requires appropriate strategies. Many countries still have high cash usage.

This study focuses on digital payment, one of the most used fintech. The definition of digital payment generally covers debit cards, credit cards, Internet payments, and mobile payments, among others. It is a cashless form of making payments. The purpose of introducing digital payment platforms is to reduce or eliminate the costs of transactions and household participation in financial markets. Thus, it is expected to contribute to positive economic outcomes.

Existing studies developed theoretical frameworks to explain the impact of introducing digital payment. Firstly, Crouzet, Gupta, and Mezzanotti (2019) extend the dynamic model of technology adoption with positive externalities. The focus is on a collection of infinitely-lived firms. In each period, the profit-maximizing firm must choose between two technologies: cash and electronic money. There is a cost when switching from cash to electronic money, but not vice versa. The profit function of electronic money includes the complementarities parameter, representing the increasing external return when other firms in the industry adopt electronic payment. The model predicts that the number of users will increase in the long run only when there are complementarities. On the other hand, the complementarities model is based on the positive relationship between technology adoption and the initial strength of complementarities. Thus, a positive shock might widen the gap among regions.

Secondly, in Agarwal et al. (2020)'s model (2020), consumers choose a payment method for transactions to maximize their utility function. Merchants make a technology adoption decision based on their expected profit function. Additionally, banks maximize profit based on the number of ATMs and credit supply. Positive externalities are modeled as a reduced form, manifested through the decreasing cost of electronic payment as the number of users increases. The model predicts that financial technology adoption increases partly due to positive externalities. The assumption that each payment method has different profit margins explains why the introduction of the QR code (electronic payment technology) leads to a reduction in the number of ATMs (lower profit margin) while credit supply via credit cards increases (higher profit margin).

Finally, Chodorow-Reich et al. (2018) developed a closed economy model with a continuum of regions. The agents in this model include households, firms, banks, and the government. Each region produces a non-traded and a unique traded good. Households consume non-traded and traded goods and hold two stores of value: cash and deposits. The demand for cash arises from a cash-in-advance (CIA) constraint and tax advantages. Banks and firms operate in a perfectly competitive environment. Banks take deposits from consumers and lend to firms and the government. Subject to working capital constraints, firms take bank loans to pay households wages. The model introduces downward (nominal) wage rigidity as a friction. The government raises funds through money creation, debt issuance, income taxes, and transfers, all to households. This model explains the increase in financial technology after demonetization when the CIA constraint binds.

Empirical findings also confirm the positive impact of digital payment. For example, Dubey and Purnanandam (2023) find the causal link between digital payments and economic outcomes based on empirical results of introducing India's Unified Payment Interface (UPI) platform. In addition, the results are also more robust in financially less developed regions of the country and for financially weaker households such as small traders.

Agarwal et al. (2020) and Agarwal et al. (2019b) studied the impact of introducing mobile payment technology, QR-code, in 2017 on business creation using a bank's transactions data and firm-level data in Singapore. They found that after the introduction, the growth of business creation among business-to-customer industries was 8.9% higher than those in business-to-business industries. Besides, the effect was more pronounced in smaller merchants and industries with high cash-handling costs. Simultaneously, using cash via ATMs was reduced, indicating that some customers have substituted mobile wallets for cash. On the other hand, customers also increased their spending by about 4.2%. The authors also observed an increase in credit card usage, which they explained was due to the increase in credit supply from the profit-maximizing bank to capture the increased customer demand.

In Mexico, the government provided a debit card to urban beneficiaries under the cash transfer program Oportunidades from January 2009 to April 2012. Based on bank transaction data and administrative data, Bachas et al. (2018) found that introducing the debit card lowered indirect transaction costs by reducing travel distance and foregone activities, such as work and childcare.

Related to this, Higgins (2020) quantified the spillovers of consumer Fintech adoption: the supply-side response feeds back to the demand side. The author found that the supply side responded to the introduction of debit card use by increasing small retailers' adoption of point-of-sale (POS) terminals. The adoption led to a 21% increase in other customers with debit cards and a 13% substitution rate from supermarkets to small-sized stores for affluent consumers. Based on the discrete-continuous choice literature, the author also measured consumer surplus and estimated that 55%-58% of the increase in consumer surplus accrued as spillovers to non-beneficiaries. However, introducing the debit card did not impact bank transaction fees or bank presence.

The 2016 demonetization in India has also served as a basis for studying the impact of digital payments. This unexpected policy caused a temporary reduction of 86% of cash in circulation, leading to the adoption of digital payments and electronic wallets by cash-dependent consumers. Crouzet, Gupta, and Mezzanotti (2019) employed a dynamic adoption model with positive externalities to explain the permanent increase in the growth rate of the user base, not just the size. Their reduced form model was estimated based on merchant-level transactions from the leading digital wallet company. The estimation revealed that 60% of the increase in the user base was due to complementarities. The model also indicated that the growth rate of the user base was higher in districts with higher initial adoption after the demonetization, which aligned with the observed data. Consequently, such policy shocks may widen the gap in financial technology adoption.

Building on the same episode, Chodorow-Reich et al. (2018) examined this policy shock's overall short-term impact using a demonetization model, where agents hold cash to fulfill both a cash-in-advance constraint and tax evasion purposes. The model was estimated using cross-sectional novel data, including ATM withdrawals, night lights (a measure of economic activities), E-wallets, and POS for credit/debit card usage. In line with the model, the estimation indicated that districts with severe cash shortages adopted E-wallets and POS more quickly. However, bank credit growth slowed down more, and economic activities were reduced.

Based on survey data of 1003 merchants in Jaipur, India, Ligon et al. (2019) found that the slow adoption of digital payments was not due to supply-side issues, as merchants could obtain the necessary infrastructure for providing the service. Instead, it stemmed from demand-side factors, such as a perceived lack of customers paying digitally and concerns that digital payments might increase tax liability.

On the other hand, some empirical analyses also find that digital payment can lead to household overconsumption and spending. Agarwal et al. (2019a), for example, using receipt-level transaction data from a supermarket chain, found that the adoption of digital payments increased customers' spending, particularly on expensive goods. The study showed that this spending increase was unrelated to credit supply, income shock, suppliers' pricing response, or consumers' shift to the formal market. This suggests that digital payment usage may lead to overspending and less effective financial planning for consumers. Moreover, based on transaction data from a leading online retail platform, a study by Bandi et al. (2019) corroborated Agarwal et al. (2019a)s findings. They discovered that consumers who switched from cash-on delivery to digital payments maintained their purchase frequency but spent more and were less likely to return their purchases. Nevertheless, Hong (2023) finds that digital payment adoption increases participation and risk-taking in mutual fund investments.

The impact of digital payment introduction is significant in public policy design. In this study, we complement existing research by conducting further investigations into the impact of digital payment introduction on household finance, with a specific focus on addressing two crucial public policy questions:

- Can the government utilize the innovation in the payment system to increase the efficiency of its transfer payment program?
- Does the innovation in the payment system encourage financial inclusion by enhancing trust and understanding of the financial market and products?

We exploit the introduction of an innovation in the digital payment system in Thailand as a quasi-experiment to examine its impact on household finance based on household socioeconomic survey data by the National Statistic Office (NSO) and individual survey data. Based on the NSO socioeconomic survey data, we find a positive impact on net household consumption due to the introduction of the cashless state welfare card. However, this effect is small and not robust.

On the other hand, our main result is that we find a statistically significant and positive impact of introducing state welfare cards on in-kind (non-cash) household consumption, which is relatively more robust than the total consumption case. This finding contradicts the claim that the grey market for the state welfare card might render the scheme ineffective by enabling people to use the card for purposes other than daily consumption.

We further analyze the impact of introducing the state welfare card on unhealthy consumption, specifically tobacco products. As expected, there is no significant impact on household tobacco product consumption. Given the limitations of the socioeconomic survey data, our estimation results align with existing studies, suggesting that innovations in the digital payment system can influence people's consumption patterns.

The relatively low statistical explanatory power can be attributed to the lag in data from the household socioeconomic survey. To address this, we complement our analysis by conducting an individual survey in four provinces of Thailand. We introduce the relevant variable of income level in 2017 as the correct running variable while also incorporating other outcome variables, such as financial literacy and trust in the digital finance system.

Incorporating income-level data from 2017 as a new data survey improves the estimation's robustness. Using income-level data from 2017 provides a better explanation for the probability of receiving the state welfare card than household-level data from 2019 or 2022. However, no significant evidence supports increased net consumption expenditure after receiving the state welfare card.

Furthermore, we utilize the same models to examine the impact of introducing the state welfare card other than on consumption. We use the financial literacy score as the outcome variable. The estimation shows that people who obtain the card understand basic finance concepts better than around 20%. One possible explanation is the training provided by the government to individuals who receive the social welfare card.

The same model estimation also reveals a reduction in household risky consumption behavior, such as gambling or underground lottery participation, around 10% after introducing the state welfare card. However, this policy change does not significantly impact trust in the digital payment system.

The following paper is organized as follows: Section 2 explains in detail the empirical setting of this study. Section 3 describes the Data and Empirical Strategy. Section 4 shows the results before we conclude in Section 5.

2 Empirical Setting

2.1 Thailand's National e-Payment Master Plan

Many countries have promoted digital payment platforms, such as Paym in the UK, OSKO/PAY ID in Australia, and PayNow in Singapore. Similarly, in Thailand, the government officially launched the National ePayment Master Plan in December 2016 to create an integrated e-payment platform for fund transfer and payment, integrating tax and social security disbursement systems. The execution of the master plan is led by the Bank of Thailand (BOT) and the Revenue Department. The main objectives of this master plan are to create a payment infrastructure that supports financial inclusion and a cashless society, reduce cash usage and payment costs, and save the expenses of printing and transporting banknotes and cheques. The private sector, primarily commercial banks, played an essential role in this project. The Thai Bankers Association, under the direction of the Payment System Committee (PSC) governed by the Bank of Thailand, has established National ITMX (National Interbank Transaction Management and Exchange), which is a developer and service provider of the electronic payment infrastructure.

There are five projects under the master plan:

- PromptPay (AnyID): to provide more convenience on money transfer by using a registered ID (mobile number or national ID) through Internet banking, mobile banking, and ATMs. The project has been implemented since October 2016.
- EDC (Electronic Data Capture) and Card Acceptance Expansion: to expand the card acceptance network and promote card adoption/usage by cutting merchant fees and new local switching networks. The project has started in September 2016.
- E-Tax: to integrate tax filing systems, provide more accurate sales records, and increase tax coverage via the electronic taxing system and the E-tax invoice system. The project was gradually implemented throughout 2016.
- Government e-Payment: to provide more accuracy and convenience and reduce cash usage in government payments by direct social welfare disbursement and social welfare database. Some pilot projects started in September 2016.

- Market Education: to provide e-payment knowledge and incentives to the general public. The project has started in 2015.

After the introduction of the master plan, the adoption of Thailand's e-Payment PromptPay has increased exponentially, as shown in both the values and the volume of transactions, especially after the commercial banks' fee reduction in March 2018. The current monthly volume and values are 600 million transactions and over 2.25 trillion THB (74 billion USD).

2.2 Introduction of the State Welcare Card

Among many initiatives, the State Welfare Card scheme has become another essential part of the government's National e-Payment Master Plan since September 2017. The Thai government has distributed the cashless welfare card to Thai people older than 18 years old and meet the criteria of having an annual income below 100,000 Baht (3,300 USD) and holding financial assets lower than 100,000 Baht. The government then transfers around 200-300 Baht (6-10 USD) to the card every month so that the cardholder can buy basic consumer goods, goods for children's education, or agricultural raw materials at the registered store Thong Far shops.x

In addition, the cardholder can use public transportation for free and receive some discount (45 Baht every three months) for cooking gas. See details in The Secretary of the Cabinet (2017). In the first three months of the scheme, 93-94% of the cardholders used the card to buy basic consumer goods (See The Secretary of the Cabinet (2018b)). The government has also launched the cardholder's occupational training program (See The Secretary of the Cabinet (2018d)). Also, Specialized Financial Institutions set up special lending schemes, including housing loans for the cardholder.

Interestingly, to further promote the cashless society, the State Welfare Card also comes with an e-wallet that allows cardholders to top up and withdraw money via ATM or at the bank branch. This e-wallet can be used to pay for most EDC machines. To allow more flexibility for the cash holder, the government changed to transfer 2/3 of the welfare amount into this e-wallet instead (see The Secretary of the Cabinet (2018c) and The Secretary of the Cabinet (2019b)). Moreover, the government transfers other welfare payments to the e-wallet directly (see for example The Secretary of the Cabinet (2018a) and The Secretary of the Cabinet (2019a)).

A similar idea has also been piloted in Australia, such as the Cashless Debit Card program. The purpose, however, is to test whether reducing the amount of cash in the community will decrease the harm caused by alcohol, gambling, and drug misuse. This trial program started in 2016 and has been applied to government welfare recipients. The program, however, operates in selected regions: the Ceduna region, South Australia; the Goldfields and East Kimberley regions, Western Australia; and the Bundaberg and Hervey Bay region, Queensland.

The government will transfer 20% of welfare payments to the regular bank account and 80% to this Cashless Debit card. Cardholders can use the card for products and services in most stores that accept ETFPOS, including online payments and mobile banking, but not for alcohol, gambling, or cash withdrawals.

	Thailand's State Welfare Card	Australia Cashless Debit Card
Scope	Countrywide	Selected trial regions
Target	Low income individuals	People under government welfare program
Purpose	To reduce economic burden of low-income individuals and promote a cashless society	To test whether reducing cash circulation will reduce the harm from misuse of alcohol, gambling, and drugs.
Instrument	Cashless debit card and e-Wallet	Cashless debit card
Active	2017-current	2016-current

In the evaluation report, Mavromaras and Moskos (2021), based on the survey and in-depth interviews in 2019, find evidence that alcohol consumption, illicit drug use, and gambling have decreased in trial areas. However, it is impossible to attribute these changes to the Cashless Debit Card policy alone or find any evidence of long-term impact. In this paper, however, we also focus on economic outcomes.

The existing studies focus on the introduction of a particular type of technology, such as mobile payment (See, for example, Agarwal et al. (2020), Agarwal et al. (2019b).), debit card and POS terminal (See, for example, Bachas et al. (2018), Higgins (2020).), and digital wallet (See, for example,Agarwal et al. (2019a), Bandi et al. (2019)). In this paper, we examine the impact of the innovation in the digital payment system on the government transfer program targeting the low-income group.

To our knowledge, the empirical setup in the present study is closest to Chodorow-Reich et al. (2018), where they studied the impact of the cash demonetization policy on digital wallets and payment via POS adoption and usage. However, the difference between this paper and Chodorow-Reich et al. (2018) is that in this paper, the introduction of new technology is considered directly, not as a result of another policy.

Based on the empirical settings, the study investigates the following hypotheses:

- Hypothesis on SWC Adoption and Consumption: The study proposes that receiving the SWC will result in a higher budget constraint each month for a representative household. If the household can use the SWC to purchase consumption goods without any problem (full adoption), they will increase their consumption accordingly. However, if the household cannot use the SWC fully or encounters difficulties, they will not increase their consumption or savings. For instance, there may be a secondary market for the SWC where households can sell the card at a discount of around 50% for cash, indicating potential challenges in fully utilizing the card's benefits.
- Hypothesis on Positive and Negative impact: The study also investigates positive and negative impacts. On the positive side, introducing the SWC may increase households' financial literacy, enhance their understanding of financial services, and improve their financial decision-making. On the negative side, there may be potential increases in alcohol, drug, or gambling consumption as unintended consequences of the SWC's implementation.

By examining these hypotheses, the study aims to shed light on the SWC's impacts on household consumption behavior, financial literacy, and potentially associated negative outcomes. This investigation will provide valuable insights into the effectiveness and challenges of the SWC program and its broader implications for social welfare and digital finance policy.

3 Data and Empirical Strategy

The paper joins a recent methodology improvement that analyzes large-scale new datasets in quasi-experimental settings, such as those of Agarwal et al. (2019b); Higgins (2020); Chodorow-Reich et al. (2018); Bachas et al. (2018). We utilize the regression discontinuity design, leveraging that individuals who receive the state welfare card must satisfy a specific arbitrary threshold of annual income and financial assets, which should be less than 100,000 baht.

3.1 Sharp Regression Discontinutity Design with SES data

By relying on the conditional independence assumption, the key to the regression discontinuity design lies in comprehending the underlying mechanism that governs the assignment of treatment D_i (State Welfare Card). In the simplified case, we assume the assignment to treatment depends solely on a single variable X_i, which is income.

Thus, in the sharp regression discontinuity design, this income variable fully determines the treatment assignment based on the cutoff rule at 100,000 THB per annum.

$$D_i = \begin{cases} 1 & \text{if } X_i \leq c \\ 0 & \text{if } X_i > c \end{cases} \tag{1}$$

We used Thailand's Household Socioeconomic Survey (SES) 2019, which the National Statistical Office conducted to conduct the study. The survey employed a stratified two-stage sampling method, with Bangkok Metropolitan and 76 Provinces being the constituted strata. In total, there were 77 strata, with each stratum (except Bangkok Metropolitan) further divided into two parts: municipal areas and non-municipal areas. The sample consisted of approximately 55,584 households, evenly divided into twelve equally representative sub-samples. This survey is considered the most comprehensive household survey in Thailand.

The survey collected detailed information on households' income, expenditures, debt, assets, and housing characteristics. The survey's expenditure data referred to expenditures on necessary items for daily life, which excluded saving and capital formation expenditures such as the purchase or hire-purchase of house and land. The survey in 2019 added the question of whether households are receiving the State Welfare Card or not.

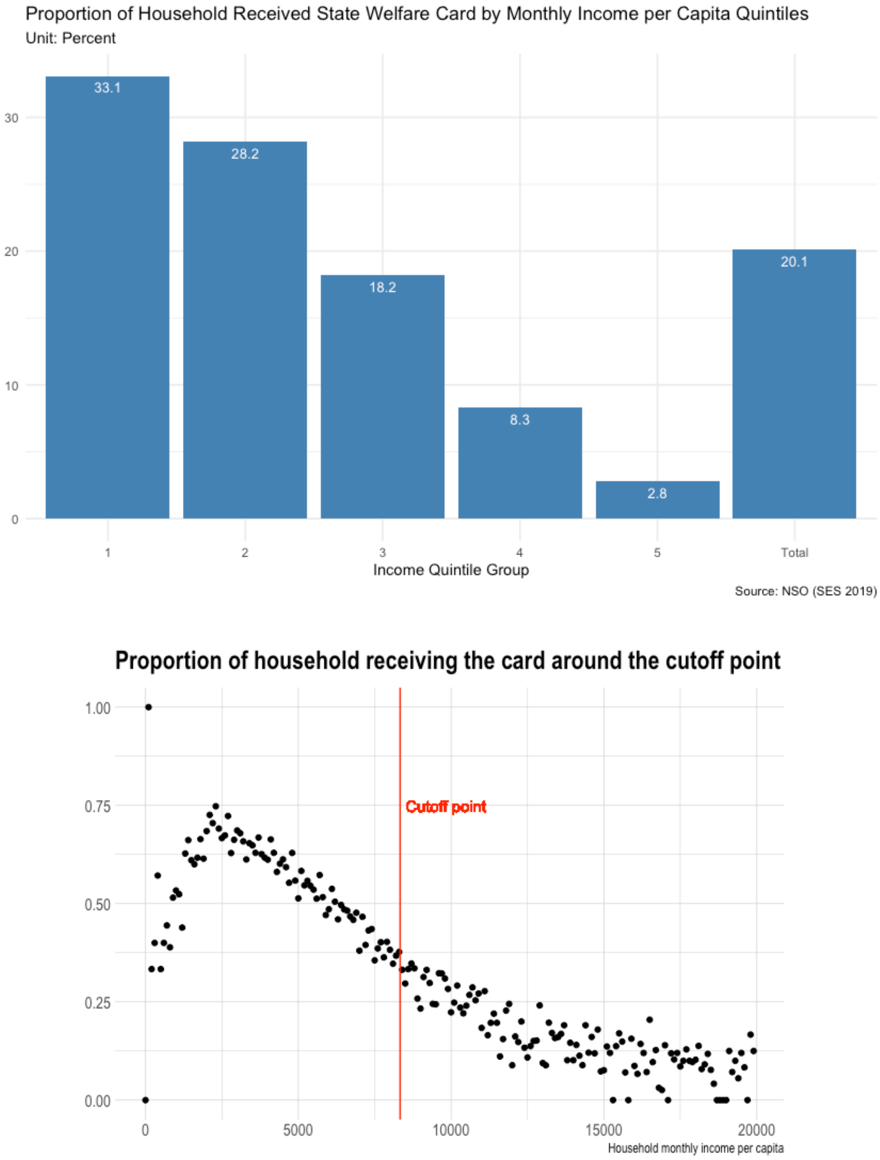
3.2 Identification Challenges

The identification challenges are twofold. First, we use the household-level survey data with the individual-level eligibility criteria. This means even high-income households can receive the Card if any member fits the eligibility criteria. Figure 1, upper panel, shows the proportion of households that received the State Welcare Card by monthly income per capita quintiles. As a result, when using the Monthly Income per Capita at 8,333.33 THB as the cutoff point, the proportion of households receiving the card is higher when the monthly income per capita is lower than the cutoff point.

Nevertheless, the proportion of households receiving the card around the cutoff point does not show discontinuity. See Figure 1 lower panel.

To address this concern, we narrowed the sample to include only single-person households and verified the presence of discontinuity around the monthly income threshold. However, even among single-person households, compliance with the eligibility rule remains a compliance issue.
Figure 2 to Figure 4 show the proportion of households receiving the card around the monthly income, the age of the household head, and the financial asset cutoff

Figure 1: Proportion of Household Received the State Welfare Card by Monthly Income per Capita Quintiles and around the cutoff point



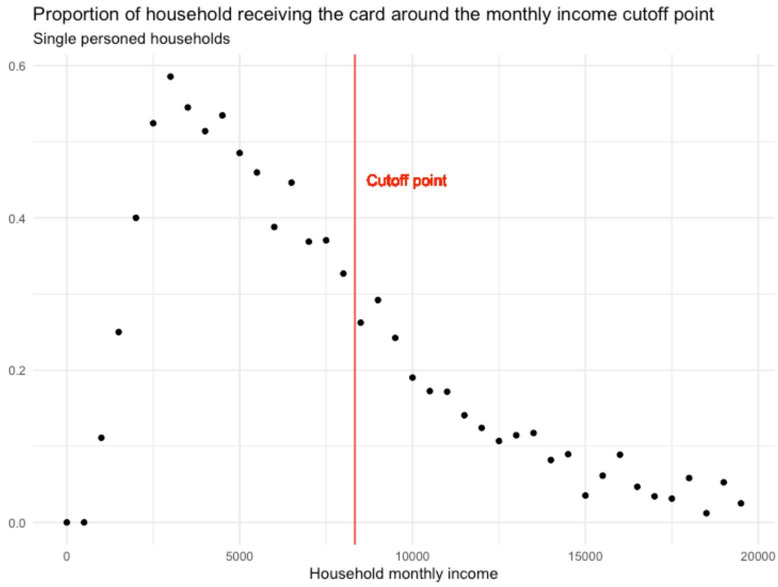
points, respectively.

One of the reasons that individuals with income and financial assets above the threshold but receive the State Welfare card might be that the eligibility rule is not strictly implemented. For this, the Thai government has confirmed that the Ministry of Finance has carefully checked the eligibility criteria from the government database. At the start of the program in 2016, about 11 million people passed the criteria out of over 14 million applicants. On the other hand, there was news about individuals who fit the eligibility criteria but did not receive the card due to a lack of awareness or understanding. Currently, the Thai government is working on reviewing the criteria to be more effective.

Another reason might be that some individuals underreported their income and financial assets when applying for the State Welfare Card but not when interviewed in the survey. This is either measurement error or income volatility, as the survey was conducted around two years after applying for the card. Income volatility is also likely due to the nature of work in the agricultural and informal sectors of low-income individuals.

Both situations make it difficult for Regression Discontinuity Designs as the forcing variables only mildly affect the treatment status. As a result, we consider the fuzzy regression discontinuity design instead.

Figure 2: Proportion of Single Personed Household Received the State Welfare Card around the monthly income cutoff point



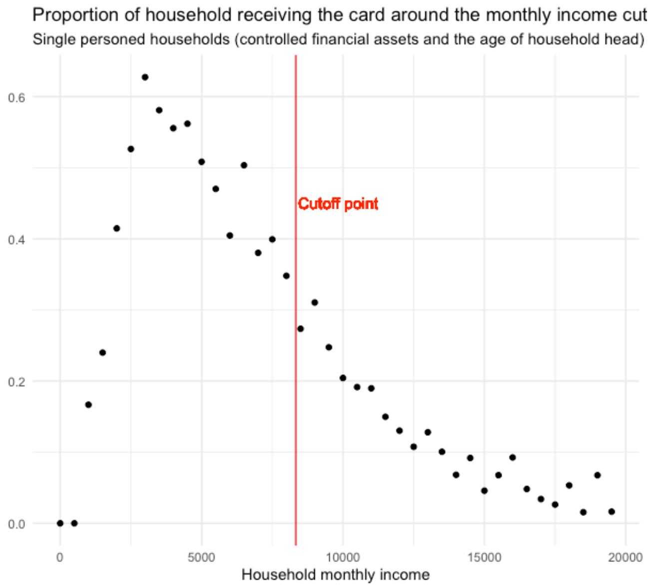
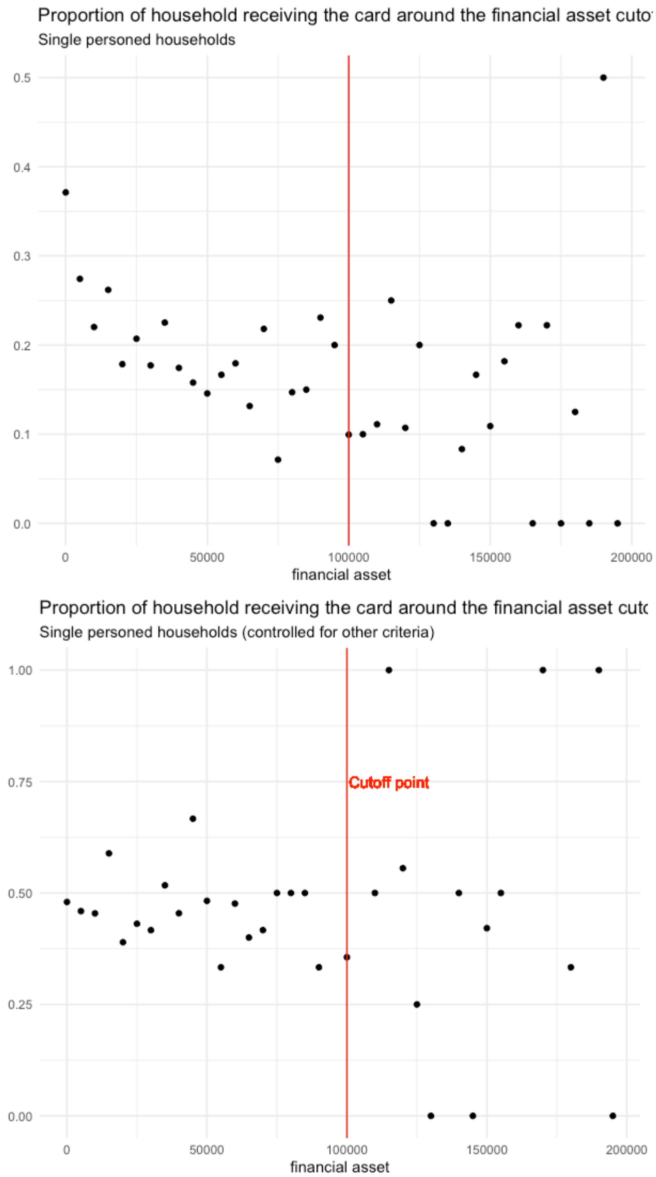


Figure 3: Proportion of Single Personed Household Received the State Welfare Card around the age of household head cutoff point

Figure 4: Proportion of Single Personed Household Received the State Welfare Card around the financial asset cutoff point



3.3 Fuzzy Regression Discontinuity Design

In this case, the treatment status (receiving the State Welfare Card) does not change 100% at the cutoff, I implement the fuzzy regression discontinuity designs. Formally,

$$0 < \lim_{x \uparrow c} \Pr(D_i = 1 | X_i = x) - \lim_{x \downarrow c} \Pr(D_i = 1 | X_i = x) < 1 \tag{2}$$

This implies:

$$\Pr(D_i = 1 | X_i \geq c) - \Pr(D_i = 1 | X_i < c) = k \tag{3}$$

where
X_i is running variable (household income)
D_i is treatment status (receiving the State Welfare Card)
c is the income cutoff
$0 < k < 1$.

3.4 Estimation method and Bandwidth Selection

To estimate the impact on outcome variable Y_i, we utilize two stage least square (Instrument Variable) method as follows:

First stage equation:

$$D_i = \alpha + \gamma 1[X_i < c] + f(X_i - c) + \nu_i \tag{4}$$

Second stage equation:

$$Y_i = \alpha + \tau \hat{D}_i + f(X_i - c) + \epsilon_i \tag{5}$$

The variations can include interaction terms and other explanatory variables accordingly.

Finally, we specify a narrow bandwidth that is close to the cutoff as: $c - h \leq X_i \leq c + h$.

In the context of Regression Discontinuity Design, selecting an appropriate bandwidth, h, or window around the cutoff point is a another challenge. This choice affects the estimation result A large bandwidth might include observations that differ significantly from the cutoff point, leading to potential bias or confounding factors. In contrast, a small bandwidth could decrease statistical power or precision, increasing the variance or uncertainty of the estimates.

We use the nonparametric method following Calonico, Cattaneo, and Titiunik (2014) for optimal bandwidth selection based on Mean Square Errors. In addition, the arbitrary choice of bandwidth is included for the robustness check.

4 Estimation results

This section presents the key estimation results obtained from the regression discontinuity design equation in (5). The first subsection, utilizing the SES 2019 data, discusses the household-level estimation results. We include both multiple-person and single-person households for comparison purposes, and the outcome variables in this section primarily focus on expenditure variables.

The second subsection presents individual-level estimation results based on the survey conducted on individuals. In addition to expenditure variables, we can include specific variables related to positive and negative spillovers, such as financial literacy, trust in the digital payment system, and gambling expenditures, thanks to the customized questionnaire used in the survey.

4.1 Household-level estimation results

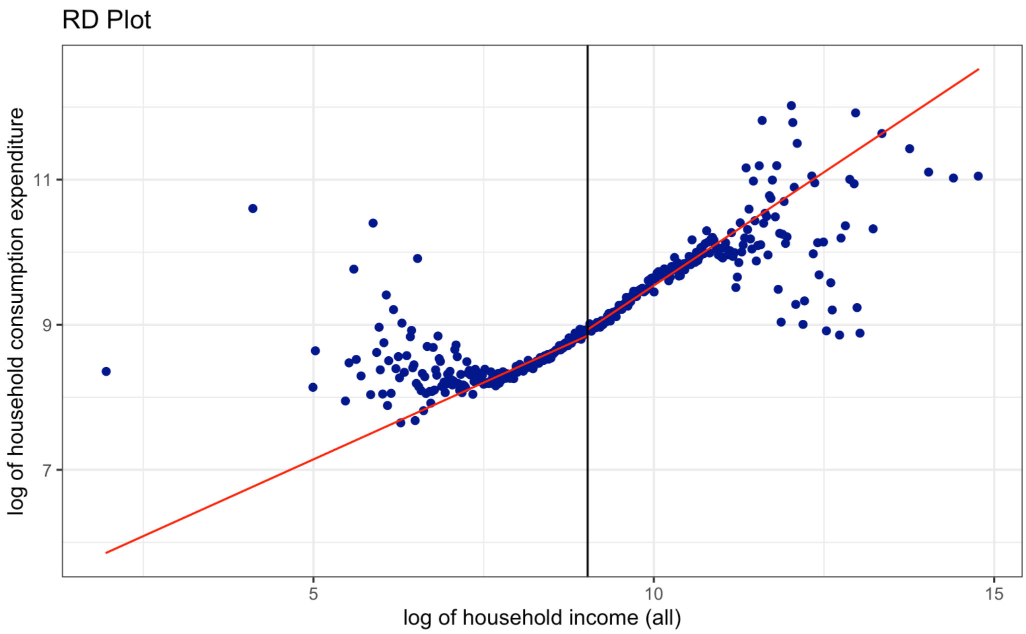
4.1.1 Total household consumption expenditure

We begin by examining the impact on total household consumption expenditure. The advantage of using the regression discontinuity design in empirical data analysis is that it enables graphical inspection of discontinuity in outcome variables. Figure 5 below illustrates the (lack of) discontinuity in total household consumption expenditure around the cutoff of the running variable, household income, for both all and single-person households.

Next, we utilize two estimation models: (i) without an interaction term and (ii) with an interaction term between the treatment variable and the running variable. For each model, we use four levels of bandwidth: two from nonparametric MSE bandwidth selection approaches (MSE for the RD Treatment effect estimator mserd, and MSE for the sum of regression estimates - msesum), and two based on the rule of thumb approach for robustness checking purposes. The results of these estimations are presented in Tables 1 and 2 for all households and single-person households, respectively.

Using all household data, both models have resulted in a positive coefficient of the treatment variable, *card*, but it is not statistically significant except when the bandwidth, h, is wide enough. This finding is consistent with the results based on the single-person household data. The non-robust result suggests a lack of statistical power of the treatment variable in explaining the increase in household consumption expenditure.

Figure 5: Lack of discontnuity in total household consumption around the cutoff of the running variable, household income.



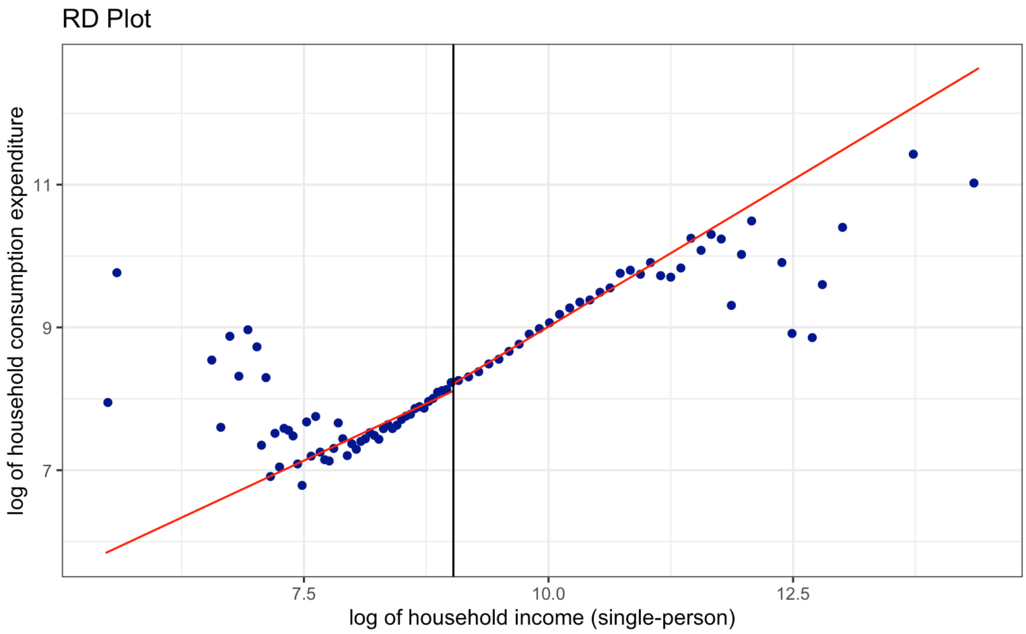


Table 1: Total household consumption expenditures - all households

	Model 1				Model 2			
h	0.41	0.397	0.5	0.6	0.41	0.397	0.5	0.6
(Intercept)	8.646***	8.518***	8.617***	8.589***	8.656***	8.542***	8.650***	8.607***
	(0.324)	(0.435)	(0.296)	(0.188)	(0.321)	(0.418)	(0.269)	(0.177)
income	0.968**	1.168*	1.007**	1.050***	0.905*	1.038*	0.907***	0.999***
	(0.467)	(0.635)	(0.415)	(0.250)	(0.464)	(0.586)	(0.350)	(0.228)
card	0.837	1.224	0.916	1.002*	0.821	1.174	0.838	0.962*
	(0.988)	(1.323)	(0.893)	(0.567)	(0.979)	(1.278)	(0.822)	(0.539)
income*card					0.164	0.314	0.185	0.094
					(0.262)	(0.328)	(0.198)	(0.130)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	18289	17699	22042	25793	18289	17699	22042	25793

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Total household consumption expenditures - single-person households

	Model 1				Model 2			
h	0.453	0.382	0.7	0.8	0.453	0.382	0.7	0.8
(Intercept)	7.965***	7.915***	8.004***	7.993***	7.954***	7.878***	7.995***	7.990***
	(0.254)	(0.336)	(0.129)	(0.101)	(0.238)	(0.324)	(0.133)	(0.101)
income	1.175***	1.262**	1.099***	1.118***	1.161***	1.216*	1.063***	1.105***
	(0.386)	(0.529)	(0.176)	(0.131)	(0.430)	(0.636)	(0.188)	(0.137)
card	0.761	0.921	0.602	0.647*	0.812	1.080	0.679	0.678**
	(0.868)	(1.137)	(0.440)	(0.345)	(0.786)	(1.065)	(0.449)	(0.344)
income*card					0.136	0.438	0.242*	0.091
					(0.416)	(0.705)	(0.130)	(0.107)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	4845	4145	6770	7356	4845	4145	6770	7356

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.1.2 In-kind consumption expenditures

Next, we examine the breakdown of household consumption in the SES data, specifically focusing on in-kind (non-cash consumption). Similar to the previous analysis, we begin with a graphical inspection of the outcome variable around the cutoff. As shown in Figure 6, there appears to be a discontinuity in in-kind consumption around the cutoff, indicating the potential positive impacts of introducing the state welfare card.

For the case of all household data, we once again estimate two models: (i) without an interaction term, and (ii) with an interaction term between the treatment variable and the running variable. Similarly to the analysis of all household consumption, in each model, we use four levels of bandwidth: two from nonparametric MSE bandwidth selection approaches (MSE for the RD Treatment effect estimator - mserd, and MSE for the sum of regression estimates - msesum), and two from the rule of thumb approach for robustness checking purposes. The estimation results are displayed in Tables 3 and 4.

For the all household data case, we find that the positive coefficient of the treatment variable, *card*, becomes significant when the bandwidth is increased to 0.5-0.6. On the other hand, the interaction terms are statistically significant for the single-person household case, with the lower bandwidths suggested by the nonparametric approach. At the same time, the coefficient of the treatment variable itself becomes significant when the bandwidth is increased further.

The results based on in-kind consumption data are more robust than those of all consumption data. This can be partly explained by the fact that the usage of the state welfare card for household consumption is all recorded as "in-kind" consumption, according to the National Statistical Office (2022). This means that when a household receives government transfers via the state welfare card, they spend on their consumption and do not entirely trade the card's value for cash in the grey market to buy unallowed items such as alcohol or tobacco.

Figure 6: Discontnuity in household in-kind consumption around the cutoff of the running variable, household income.

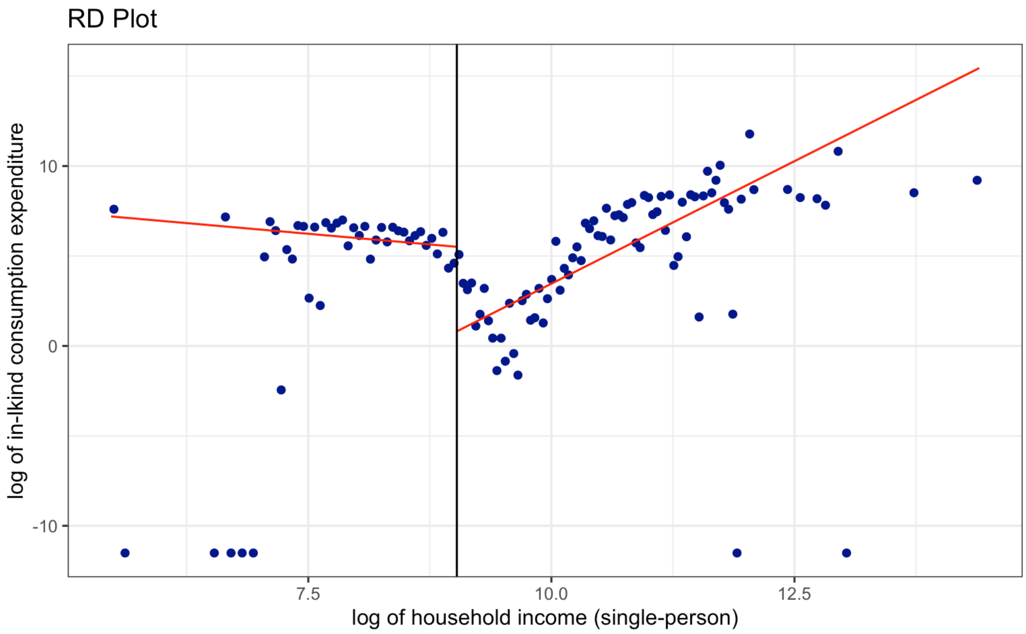


Table 3: In-kind consumption expenditures - all households

	Model 1				Model 2			
h	0.391	0.376	0.5	0.6	0.391	0.376	0.5	0.6
(Intercept)	-8.435	-6.964	-6.358	-5.456*	-7.505	-6.495	-4.232	-4.148
	(9.738)	(8.568)	(5.611)	(3.220)	(9.034)	(8.345)	(4.541)	(2.830)
income	13.625	11.332	10.022	8.673**	8.702	7.156	3.477	4.958
	(14.318)	(12.637)	(7.866)	(4.275)	(12.651)	(12.182)	(5.972)	(3.673)
card	39.571	35.157	32.714*	29.985***	37.615	34.526	27.654**	27.043***
	(29.580)	(26.086)	(16.935)	(9.712)	(27.630)	(25.470)	(13.876)	(8.598)
income*card					11.788*	11.602*	12.066***	6.832***
					(6.701)	(6.363)	(3.201)	(2.011)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	17445	16811	22042	25793	17445	16811	22042	25793

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 4: In-kind consumption expenditures - single personed households

	Model 1				Model 2			
h	0.334	0.342	0.7	0.8	0.334	0.342	0.7	0.8
(Intercept)	-2.722	-0.049	-4.197	-6.768**	-3.045	-0.583	-4.456	-6.813**
	(12.600)	(10.071)	(3.181)	(3.024)	(13.148)	(10.489)	(3.295)	(3.027)
income	1.212	-3.671	1.703	5.763	-1.206	-6.657	0.733	5.583
	(21.248)	(16.952)	(4.340)	(3.933)	(22.536)	(18.154)	(4.722)	(4.084)
card	19.866	10.865	23.716**	32.764***	21.632	13.585	25.859**	33.205***
	(41.800)	(33.413)	(10.864)	(10.388)	(43.593)	(34.725)	(11.088)	(10.284)
income*card					11.290	14.909	6.681**	1.288
					(11.828)	(9.361)	(3.234)	(3.143)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	3608	3678	6770	7356	3608	3678	6770	7356

* p < 0.1, ** p < 0.05, *** p < 0.01

4.1.3 Food and beverage consumption expenditures

The primary target of government transfers is the daily consumption of goods. In the following analysis, we examine the impact on two groups of daily consumption: food and beverage and tobacco products.

Focusing on food and beverage consumption, we employ the same estimation model used in the analysis of total and in-kind household consumption. The results are presented in Tables 5, 6, 7 and 8. Once again, for the in-kind consumption analysis, the coefficient of the treatment variable is statistically significant for both the case of all households and single-person households. The robustness of these results appears better than for all food and beverage consumption cases.

Table 5: Food and beverage consumption expenditures - all households

	Model 1				Model 2			
h	0.437	0.41	0.5	0.6	0.437	0.41	0.5	0.6
(Intercept)	9.511***	8.950***	9.269***	8.714***	9.577***	8.976***	9.349***	8.777***
	(0.691)	(0.411)	(0.466)	(0.199)	(0.697)	(0.419)	(0.467)	(0.200)
income	-1.152	-0.262	-0.779	0.056	-1.407	-0.428	-1.026	-0.121
	(1.004)	(0.597)	(0.662)	(0.266)	(0.982)	(0.645)	(0.643)	(0.277)
card	-2.579	-0.857	-1.849	-0.169	-2.732	-0.900	-2.040	-0.309
	(2.098)	(1.252)	(1.410)	(0.602)	(2.130)	(1.272)	(1.427)	(0.605)
income*card					0.535	0.434	0.455	0.325**
					(0.519)	(0.367)	(0.342)	(0.153)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	19454	18289	22042	25793	19454	18289	22042	25793

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Food and beverage consumption expenditures - single-person households

	Model 1				Model 2			
h	0.547	0.589	0.7	0.8	0.547	0.589	0.7	0.8
(Intercept)	8.239***	8.306***	7.868***	7.764***	8.208***	8.236***	7.858***	7.762***
	(0.426)	(0.458)	(0.318)	(0.247)	(0.404)	(0.410)	(0.313)	(0.243)
income	-0.049	-0.160	0.554	0.718**	-0.277	-0.385	0.516	0.708**
	(0.628)	(0.685)	(0.429)	(0.310)	(0.743)	(0.790)	(0.460)	(0.330)
card	-0.737	-0.969	0.546	0.912	-0.469	-0.546	0.630	0.935
	(1.463)	(1.579)	(1.079)	(0.836)	(1.316)	(1.327)	(1.033)	(0.800)
income * card					1.231	1.478	0.262	0.068
					(0.809)	(0.954)	(0.318)	(0.237)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	5665	5526	6770	7356	5665	5526	6770	7356

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: In-kind food and beverage consumption expenditures - all households

	Model 1				Model 2			
h	0.381	0.760	0.5	0.6	0.381	0.760	0.5	0.6
	(5.561)	(1.748)	(4.419)	(2.787)	(5.388)	(1.564)	(3.952)	(2.562)
income	0.809	1.726	1.743	2.250	-2.820	-0.813	-0.874	-0.209
	(8.045)	(2.153)	(6.193)	(3.699)	(7.918)	(1.879)	(5.172)	(3.323)
card	19.563	21.401***	21.420	22.430***	15.124	19.006***	19.397	20.482***
	(16.880)	(5.227)	(13.336)	(8.405)	(16.433)	(4.732)	(12.090)	(7.790)
income*card					4.117	4.220***	4.824*	4.524**
					(4.216)	(1.127)	(2.852)	(1.832)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	20033	31212	22042	25793	17020	31212	22042	25793

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: In-kind food and beverage consumption expenditures - single-person households

	Model 1				Model 2			
h	0.334	0.505	0.7	0.8	0.334	0.505	0.7	0.8
(Intercept)	-5.049	-6.034	-10.227***	-10.585***	-4.911	-6.073	-10.190***	-10.535***
	(12.200)	(4.135)	(3.502)	(2.733)	(12.196)	(3.969)	(3.454)	(2.690)
income	-7.463	-6.039	0.793	1.374	-6.432	-6.145	0.936	1.574
	(20.562)	(6.073)	(4.765)	(3.552)	(20.855)	(6.612)	(4.874)	(3.629)
card	8.472	11.735	26.009**	27.284***	7.719	11.954	25.695**	26.797***
	(40.481)	(14.081)	(11.965)	(9.387)	(40.453)	(13.165)	(11.691)	(9.138)
income*card					-4.817	0.734	-0.979	-1.423
					(10.962)	(5.817)	(3.359)	(2.806)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	3608	5313	6770	7356	3608	5313	6770	7356

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.1.4 Tobacco product consumption expenditures

Finally, we verify the impact on an unhealthy product, tobacco, which is not legally allowed to be purchased using the state welfare card. From the estimation results for all tobacco product household consumption, there is no significant change due to the introduction of the state welfare card. Similarly, this is also the case for in-kind tobacco consumption. See Tables 9, 10, 11, 12 below for details.

The analysis of household-level data shows that using the social welfare card mainly involves in-kind consumption expenditure through food and beverage consumption. However, the results are not very robust. On the other hand, the impact on household consumption is positive and consistent with the existing literature in both all household data and single-person household data. However, there is no evidence of a negative impact, such as an increase in tobacco product consumption, through this policy.

Nevertheless, the results are not statistically robust. Although we narrowed down the analysis to single-person households, this only partially resolves the identification issue. In the following subsection, we utilize individual-level survey data from 4 provinces in Thailand to investigate the spillovers of this policy further. Additionally, we introduce the new variable, income as of 2017, the year the state welfare card was granted, to address the issue of income volatility.

Table 9: Tobacco product consumption expenditures - all households

	Model 1				Model 2			
h	0.705	0.595	0.5	0.6	0.705	0.595	0.5	0.6
(Intercept)	-11.477***	-11.499***	-8.835**	-11.354***	-11.565***	-11.840***	-9.604***	-11.706***
	(1.342)	(1.841)	(3.525)	(1.870)	(1.260)	(1.753)	(3.122)	(1.771)
income	-2.713	-2.640	-6.617	-2.853	-2.492	-1.654	-4.250	-1.854
	(1.693)	(2.446)	(4.943)	(2.485)	(1.531)	(2.266)	(4.053)	(2.282)
card	-2.535	-2.396	-10.426	-2.833	-2.342	-1.637	-8.596	-2.042
	(4.024)	(5.552)	(10.637)	(5.638)	(3.832)	(5.334)	(9.560)	(5.393)
income*card					-0.385	-1.844	-4.365*	-1.837
					(0.961)	(1.323)	(2.333)	(1.310)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	29472	25639	22042	25793	29472	25639	22042	25793

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Tabacco product consumption expenditures - single-person households

	Model 1				Model 2			
h	0.462	0.362	0.7	0.8	0.462	0.362	0.7	0.8
(Intercept)	-15.831***	-14.783***	-13.109***	-12.693***	-14.393***	-14.393***	-13.051***	-12.649***
	(3.810)	(3.472)	(1.893)	(1.452)	(3.093)	(3.093)	(1.880)	(1.444)
income	3.884	2.144	-0.530	-1.161	2.653	2.653	-0.313	-0.985
	(5.823)	(5.283)	(2.589)	(1.896)	(5.586)	(5.586)	(2.676)	(1.970)
card	8.074	4.922	-0.744	-2.128	3.089	3.089	-1.225	-2.559
	(12.768)	(11.879)	(6.467)	(4.981)	(10.230)	(10.230)	(6.354)	(4.887)
income*card					-4.881	-4.881	-1.497	-1.260
					(5.425)	(5.425)	(1.882)	(1.552)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	3883	4920	6770	7356	4920	4920	6770	7356

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Tabacco product in-kind consumption expenditures -all households

	Model 1				Model 2			
h	0.448	0.334	0.5	0.6	0.448	0.334	0.7	0.8
(Intercept)	-14.978***	-14.661***	-15.091***	-15.359***	-15.017***	-14.782***	-15.175***	-15.427***
	(0.871)	(1.282)	(0.736)	(0.417)	(0.831)	(1.185)	(0.667)	(0.391)
income	-1.530	-2.021	-1.347	-0.937*	-1.374	-1.228	-1.090	-0.746
	(1.241)	(1.900)	(1.029)	(0.553)	(1.126)	(1.604)	(0.868)	(0.501)
card	-3.046	-3.989	-2.682	-1.861	-2.959	-3.727	-2.484	-1.709
	(2.636)	(3.884)	(2.217)	(1.253)	(2.535)	(3.625)	(2.038)	(1.188)
income*card					-0.339	-1.972	-0.474	-0.351
					(0.587)	(1.371)	(0.483)	(0.288)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	19948	14981	22042	25793	19948	14981	22042	25793

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 12: Tabacco product in-kind consumption expenditures - single-person households

	Model 1				Model 2			
h	0.431	0.407	0.7	0.8	0.431	0.407	0.7	0.8
(Intercept)	-14.440***	-14.404***	-15.680***	-15.801***	-14.493***	-14.478***	-15.666***	-15.793***
	(1.298)	(1.184)	(0.403)	(0.302)	(1.130)	(0.978)	(0.403)	(0.301)
income	-2.697	-2.760	-0.615	-0.431	-2.760	-2.853	-0.564	-0.401
	(1.981)	(1.797)	(0.547)	(0.389)	(2.074)	(1.931)	(0.566)	(0.399)
card	-5.242	-5.364	-1.006	-0.599	-5.003	-5.040	-1.119	-0.673
	(4.416)	(4.040)	(1.371)	(1.031)	(3.716)	(3.197)	(1.355)	(1.017)
income*card					0.628	0.880	-0.352	-0.217
					(2.242)	(2.717)	(0.427)	(0.332)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	4614	4384	6770	7356	4614	4384	6770	7356

* p < 0.1, ** p < 0.05, *** p < 0.01

4.2 Key results from the individual-level survey data

Using the SES 2019 data for this study reveals a potential drawback in our estimation, as the non-compliance ratio remains high even for single-person households. This could be attributed to income volatility, given that SES data lagged two years. To address this issue, we should utilize income data as of 2017 to determine the treatment group's assignment accurately.

Furthermore, the SES 2019 data lacks important information required for this study. To supplement this limitation, a survey was conducted on approximately 256 individuals whose income in 2017 was around the threshold. These individuals were selected from the population residing in four provinces of Thailand: Chainat, Saraburi, Suphanburi, and Singburi, from March to June 2022. The survey also includes tests for financial literacy, trust in digital payment systems, and other potential spillover effects.

4.2.1 Total consumption expenditures - individuals

For the individual survey data, we conduct estimation using two different models, each employing different running variables: (i) 2022 income, and (ii) 2017 income. Both models include one or two additional explanatory variables. Similar to the analysis of household-level data, we use four levels of bandwidth in each model: two from nonparametric MSE bandwidth selection approaches (MSE for the RD Treatment effect estimator - mserd, and MSE for the sum of regression estimates - msesum), and two from the rule of thumb approach for robustness checking purposes.

The first outcome variable considered is total consumption expenditures. However, we do not find a significant impact on total consumption expenditures consistent with the household-level estimation results. For more details, refer to Table 13.

Table 13: Total consumption expenditures - individuals

	Model 1				Model 2			
h	0.470	0.359	0.5	0.6	0.587	0.459	0.5	0.6
(Intercept)	8.488***	8.562***	8.463***	8.437***	8.961***	8.916***	8.921***	8.982***
	(0.451)	(0.421)	(0.548)	(0.516)	(0.291)	(0.245)	(0.264)	(0.293)
income	1.558**	1.377*	1.621*	1.639**	0.838*	1.083**	1.105**	0.868**
	(0.723)	(0.718)	(0.931)	(0.735)	(0.471)	(0.528)	(0.533)	(0.435)
card	1.048	0.875	1.111	1.120	-0.155	-0.089	-0.073	-0.216
	(1.173)	(1.135)	(1.428)	(1.278)	(0.733)	(0.640)	(0.680)	(0.728)
income_2017					-0.317	-0.415	-0.423	-0.413
					(0.990)	(0.974)	(1.026)	(0.940)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	117	114	119	134	121	104	108	126

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2.2 Financial literacy- individuals

Another intriguing aspect is the positive effects of introducing the state welfare card within the new digital payment system. Most of the questions used to evaluate financial literacy are sourced from surveys conducted by the Bank of Thailand and the National Statistical Office. These questions assess individuals' basic understanding of finance.

Among the two models considered, we observe that the estimation result from Model 2(See Table 14, which utilizes income data from 2017, shows a positive coefficient for the treatment variable. The total score for the financial literacy test is 8, so a difference of more than 20% is quite significant. Furthermore, this result appears robust across different criteria for bandwidth selection. We attribute this finding to the financial knowledge training program organized by the government for the recipients of the state welfare card.

Table 14: Financial literacy scores - individuals

	Model 1				Model 2			
h	0.291	0.271	0.5	0.6	0.484	0.409	0.5	0.6
(Intercept)	0.909	-2.792	3.352*	3.501*	1.998***	2.044***	1.108	2.069***
	(3.276)	(9.904)	(1.733)	(1.774)	(0.660)	(0.669)	(0.844)	(0.641)
income	4.322	10.358	0.943	0.795				
	(3.875)	(14.077)	(1.047)	(0.829)				
card	3.130	8.008	0.188	0.031	1.923**	1.865**	3.644***	1.824**
	(4.156)	(13.278)	(2.204)	(2.132)	(0.873)	(0.884)	(1.288)	(0.772)
education_level	0.784**	1.155	0.539**	0.523**	0.652***	0.639***	0.646***	0.655***
	(0.340)	(1.039)	(0.248)	(0.259)	(0.118)	(0.119)	(0.145)	(0.115)
internet_use	0.614	2.086	-0.286	-0.308	0.172	0.185	0.497	0.134
	(1.330)	(3.818)	(0.557)	(0.535)	(0.417)	(0.440)	(0.477)	(0.401)
income_2017					0.656	0.600	2.211*	0.692
					(0.609)	(0.591)	(1.204)	(0.422)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	92	87	119	134	119	115	119	134

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2.3 Risk taking- individuals

Next, we delve into the potential adverse effects, which have been criticized for many cash or cashless transfer programs due to concerns about inducing risk-taking behaviors. To explore this aspect, we examine the expenditures on underground lottery from the individual survey data.

The results from Model 2 (see Table 15 for details) oexhibit statistical significance in the coefficient of the treatment variable. This underscores the importance of using the correct running variable in model estimation. Interestingly, individuals who receive the card show lower risk-taking behaviors, as indicated by a negative coefficient of around 10%. Moreover, this finding is quite robust. This reduction in risk-taking behaviors may relate to the financial literacy training provided to the recipients of the state welfare card.

Table 15: Glambing expenditure - individuals

	Model 1				Model 2			
h	0.311	0.243	0.5	0.6	0.484	0.409	0.5	0.6
(Intercept)	16.078	31.589	3.267	8.933	8.354**	7.703**	8.917**	7.305**
	(33.786)	(122.516)	(8.733)	(9.303)	(3.642)	(3.342)	(3.608)	(3.500)
income	-13.210	-44.709	7.611	-0.781				
	(47.260)	(201.839)	(6.304)	(5.520)				
card	-18.298	-42.189	-2.049	-11.389	-9.873*	-8.755*	-10.068**	-9.317**
	(44.071)	(166.754)	(11.337)	(11.560)	(5.015)	(4.431)	(4.987)	(4.671)
education_level	-3.202	-5.019	-1.714	-2.581**	-2.463***	-2.379***	-2.483***	-2.381***
	(3.502)	(12.470)	(1.167)	(1.234)	(0.697)	(0.673)	(0.698)	(0.675)
internet_use	-2.683	-6.965	0.893	0.749	0.143	0.295	-0.350	1.159
	(11.787)	(42.740)	(3.220)	(3.386)	(2.447)	(2.379)	(2.472)	(2.344)
income_2017					1.504	2.664	1.216	-0.007
					(2.841)	(2.080)	(2.902)	(2.626)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	97	85	119	134	122	124	119	134

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2.4 Trust in digital payment system- individuals

Finally, we also investigate the impact on trust in the financial system. Based on the same questionnaires used by the National Statistical Office, neither model shows any significant improvement in trust after people receive the card. The only significant variable is education level in Model 2. Please refer to Table 16 for more details. This is not entirely unexpected as trust by concept takes longer time to gain.

Table 16: Trust in digital payment system - individuals

	Model 1				Model 2			
h	0.352	0.390	0.5	0.6	0.566	0.608	0.5	0.6
(Intercept)	3.854**	3.434***	3.476***	3.091***	2.448***	2.541***	2.193**	2.541***
	(1.712)	(1.049)	(1.193)	(1.015)	(0.865)	(0.802)	(0.922)	(0.802)
log_income_centered	-1.238	-0.828	-0.891	-0.199				
	(1.518)	(0.740)	(0.833)	(0.585)				
CARDY	-1.498	-1.150	-1.204	-0.416	0.478	0.345	0.850	0.345
	(2.163)	(1.363)	(1.610)	(1.308)	(1.402)	(1.273)	(1.435)	(1.273)
EDUCATION	0.013	0.060	0.070	0.118	0.167**	0.154**	0.160**	0.154**
	(0.196)	(0.140)	(0.155)	(0.129)	(0.064)	(0.062)	(0.067)	(0.062)
INTERNET_USAGEY	0.207	0.404	0.382	0.424	0.623	0.585	0.773	0.585
	(0.761)	(0.476)	(0.449)	(0.376)	(0.431)	(0.408)	(0.477)	(0.408)
log_income_centered_5Y					-0.021	-0.152	0.461	-0.152
					(1.224)	(1.061)	(1.250)	(1.061)
bwmodel	mserd	msesum			mserd	msesum		
Num.Obs.	104	111	119	134	120	126	108	126

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

This paper investigates the impact of introducing a new digital payment innovation in Thailand on household finance using a quasi-experiment. Initially, the focus is on household consumption, revealing a small and somewhat unstable positive impact on total consumption due to the introduction of the cashless state welfare card. However, there is a more robust and statistically significant positive impact on in-kind (non-cash) household consumption, contradicting concerns about misuse in the grey market.

The study further explores the effects on specific areas like food and beverage consumption, primarily noting non-cash transactions associated with the state welfare card. No significant impact is observed regarding unhealthy consumption, like tobacco products, aligning with similar studies suggesting that digital payment innovations can influence consumption patterns.

To address the limitations of using household survey data, we conduct additional surveys in four provinces, incorporating income levels from 2017 to improve estimations. However, no significant evidence supports an increase in net consumption expenditure after receiving the state welfare card.

On the other hand, the research finds that individuals obtaining the card exhibit improved financial literacy, potentially due to government-provided training. Additionally, there is a reduction in household risk-taking behaviors postintroduction of the card, notably in activities like gambling. However, this policy change has no significant impact on trust in the digital payment system.

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