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Monetary and Economic Department

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What can 20 billion financial transactions tell us about the impacts of COVID-19 fiscal transfers?

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Abstract

We investigate the impacts of fiscal transfers on households during the COVID-19 recovery period using a novel transaction-level money transfer dataset. The study focuses on direct fiscal transfers in 2021 that occurred as a result of the second major wave of COVID-19 in Thailand and analyzes spending patterns for the recipients. We group the recipients by income levels and analyze patterns at the monthly and daily levels. The two main research questions are: (1) How much more spending did the groups make as a proportion of the fiscal stimulus? and (2) Did the stimulus make-up for lost spending during lock-down? We find that overall the recipients spent, on average, 40% of the money received over the first six days and 49% accumulatively over the first three months compared to a matched control group with similar characteristics. Unsurprisingly, the lower income group spent the highest proportion of the money received and the fiscal injection more than covered up for their lost spending during the lock-down period.

Keywords: Impacts of fiscal transfers, COVID-19, transaction-level data
JEL Codes: D12, H31, C55
Topics: Household Behaviors, Fiscal policy, Econometric Modeling

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1 Introduction

The COVID-19 pandemic has had significant and far-reaching consequences; not only on public health, but also on the economy. The contraction in economic activity due to lock-downs led to job losses and financial hardships for a large number of households. In order to mitigate the adverse impacts on households, authorities resort to fiscal, monetary, and financial measures to provide assistance to those in need. One of the most widely leveraged fiscal measures is the provision of direct cash transfers to individuals[1]. Our paper examines the patterns of income and expenditures of the recipients of direct fiscal transfers. This offers insightful perspectives to the impacts of transfers on household financial well-being.

Thailand's economy was disproportionately impacted by the COVID-19 pandemic. Two of the largest drivers of the economy, tourism and exports of goods, drastically shrunk due to poor global demand and lock-downs. As a response to the first wave of COVID-19, the government initiated a program of direct transfers starting in April 2020, where 3 monthly payments of 5,000 THB were dispersed; targeting workers in the informal sector. The second major wave of COVID-19 struck Thailand in the middle of 2021; the government expanded its support by sending out 5,000 to 15,000 THB in direct transfers to those registered in the social security program who resided in areas affected by lock-downs.

The transaction-level dataset allows us to study patterns of income and expenditures before and after the cash transfers. Given the time span of our dataset from July 2020 and December 2021, we choose to perform an event study on the fiscal transfers made in 2021. This enables us to observe the expenditures leading up to the second wave of COVID-19, during the lockdown period of the second wave itself, and after the targeted cash transfers were made. With this event study, we wish to answer two research questions: (1) Did the transfers have statistically positive impacts on spending? and (2) Did the transfers compensate for lost expenditures during lock-downs?

We quantify the results first by using OLS regressions, then a more granular analysis using control/treatment matching. Overall, we find positive relationships between transfers and additional spending. Compared to the control group, the recipients on average spent

[1]The literature on this topic is rich and has shown improvements in economic outcomes; for example, Egger et al. (2022) and Bastagli et al. (2019)

40% of received transfers in the following 5 days and 49% in the following three months after the cash injection. There is a large degree of heterogeneity, as expected, with stronger positive effects and higher spending rates for lower-income individuals. For the second research question, we observe that the fiscal transfers more than made up for lost spending for lower-income individuals, making them spend more in the whole period than those who did not reside in the lock-down areas.

In addition to COVID-19 specific transfers, we also observe recurring payments for the Old Age Allowance (OAA), the Child Support Grant (CSG), and the Disability Allowance (DA) programs. We provide the profiles of the recipients for each of the main transfer programs. We find that the profiles are in line with the targeted groups specified by the government.

The organization of the paper is as follows. Section 2 reviews the literature regarding the impacts of cash transfers to individuals or households that were implemented during the COVID-19 pandemic. Section 3 describes the proprietary transaction-level data that was compiled from the largest banks in Thailand. Section 4 delves into the different programs of fiscal transfer instituted in 2020 and 2021 that were identified using our comprehensive dataset. We then visually demonstrate and quantify the impacts of the transfers, both at the monthly-level in Section 5, and daily-level in Section 6. In the concluding section, we synthesize key findings and provide policy recommendations that can further improve fiscal responses to future crises.

2 Literature Review

This paper joins a fast-growing literature on the effects of the COVID-19 pandemic on consumer spending using transactions data. The initial lock-downs caused sharp declines in consumption, as evidenced by data from China (Chen et al. 2021), Europe (Andersen et al. 2022, Carvalho et al. 2021, Bounie et al. 2023), and the United States (Cox et al. 2020). These researchers were able to analyze and quantify many aspects of consumer behaviors, but in summary, the observed aggregate spending was estimated to have declined by between 25% and 60% in the weeks and months following imposition of lock-downs.

Governments responded to this decline in economic activity by providing fiscal packages, from healthcare expenditures increases, tax relief, subsidies, and direct cash transfers. Our paper focuses on the impacts of direct cash transfers during the pandemic. The empirical literature can be broken down into two strands, one using survey data, and the other using transaction data.

Survey-based analyses of the impacts of COVID-19 cash transfers were performed by Jaroszewicz et al. (2022) and Coibion et al. (2020) in the United States, Banerjee et al. (2020) in Kenya, and Bui et al. (2022) in Thailand and Vietnam. Jaroszewicz et al. (2022) and Banerjee et al. (2020) set up their own field experiments to test the concepts of universal basic income and unconditional cash transfers while the rest simply conduct surveys based on recent government transfers. In general, literature suggests that cash transfers improve well-being and spending, particularly in the short term. The results from Bui et al. (2022) is geographically most relevant to our paper, and they calculated that the Thai population were 11% more likely to have bought durable goods after receiving financial support from the government in 2020.

Baker et al. (2020) analyzed the spending responses to the CARES ACT of roughly 40,000 US households using high-frequency transaction data from a personal finance mobile application. They found that household spending increased by 0.25-0.40 USD per dollar received during the first week. This paper points out that liquidity is a key determinant of the heterogeneity in marginal propensity to consume (MPC) and poor households with greater income drops and lower levels of liquidity had stronger MPC responses to the stimulus. Karger & Rajan (2020) also analyzed roughly 20,000 recipients of the US fiscal transfer by using transaction-level bank account data. They estimated the MPC to be as high as 60% for those living paycheck-to-paycheck and only 24% for savers with higher incomes.

Also using transaction-level data, Kaneda et al. (2021) looked at spending patterns of over 200,000 recipients of Japanese fiscal transfers using data from a personal finance management mobile application. They reported lower MPC than those observed in the US, only 16%, but also found heterogeneity in the responses depending on liquidity constraints. The heterogeneity that can be observed using transaction-level data supports the shift of moving from representative economic models towards models with heterogeneity such as those developed in Kaplan et al. (2020) and Bayer et al. (2023).

3 Data

The dataset in this study are transaction-level money transfers originating from the five largest banks[2] in Thailand between July 2020 and December 2021. With these banks being dominant players in the space, the data covers nearly 80% of all money transfers in the Thai banking system. Money transfers in our dataset include transactions made at the branch or through electronic channels: ATM, mobile, and internet banking. The contactless nature of electronic payments meant that their adoption has accelerated during the COVID-19 pandemic at the expense of cash usage as individuals strived to maintain social-distancing[3]. This is reflected in the number of transactions observed in the dataset, which started at roughly 800 million monthly transactions in July 2020 and ended at just over 1.5 billion monthly transactions in December 2021. This is shown in Figure 1.

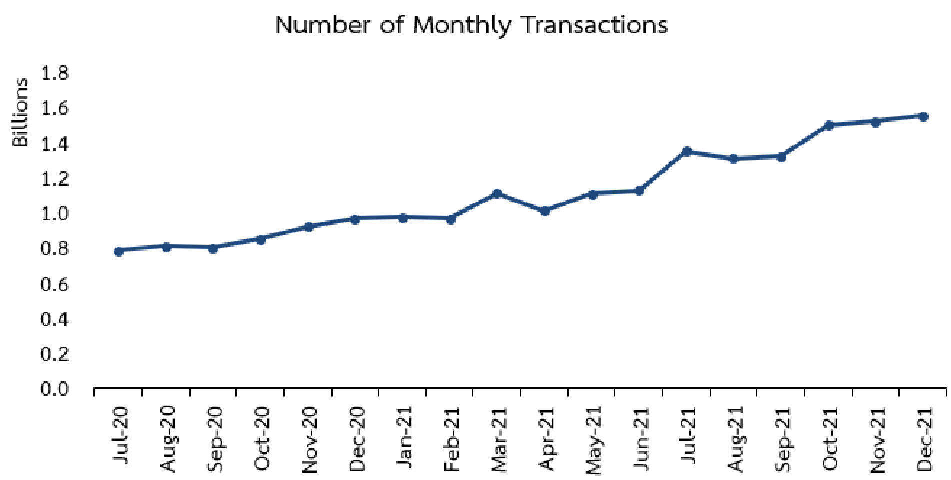

Figure 1: The number of monthly transactions that are captured in our dataset.

The data captured for each transaction include many different aspects: the transaction amount, transaction purpose (where available), bulk payment flag (mainly used for payroll payments), and channel of transaction (through a branch, an ATM, or by internet/mobile

[2]Bangkok Bank, Kasikorn Bank, Krungthai Bank, Siam Commercial Bank, and Bank of Ayudhya.

[3]Observed by Agur et al. (2020) across both developed and emerging markets.

phone). Each transaction is stamped with a date and time, down to the second. The sending bank and the bank account number are registered, along with the receiving bank and the corresponding bank account number. If the transfer is made via the recipient's national identification number, as could be the case if the transfer is made through the national digital payment program (Promptpay), then the ID number is available instead of the recipient's bank account number.

The unique aspect of this dataset is that we also have the profile information available for senders and recipients if they have an account at one of the largest five banks[4]. We are able to obtain both the senders' and recipients' profile information for 79% of all transactions. The profile information includes the zip codes of three addresses (where available): mailing address, workplace address, and registered address according to the national ID card. If the profile is for an individual, it will contain the gender, year of birth, income, education level, and occupation. If the profile is registered to a firm, it will instead contain the International Standard Industrial Classification of All Economic Activities (ISIC) code, allowing us to pinpoint the specific industry the firm is operating in[5].

Despite having a rich transaction-level dataset, there are limitations. First, it does not include other forms of payments: cash, cheques, and credit card transactions[6]. Despite the push towards electronic payments, the usage of cash still plays an important role in the Thai economy. Second, the dataset may be biased as it only includes payments originating from the five largest banks. Lastly, the profile information from the banks may not be up to date. There is a reasonable chance that the last time an individual updates his/her income and occupation information may be the time he/she opened an account.

Figure 2 plots the distributions of the logarithm, to base 10, of averaged inflows and outflows over the last nine months in 2021 of a one million samples. The log normal distributions suggest highly right-skewed inflows and outflows. As a result, expenditure outlier removal is necessary in later analyses to avoid unreliable results.

[4]Since the data is based on the sending bank, we have profiles of all senders but not all recipients.

[5]In addition, if the transaction is performed in-branch or at an ATM, we can specify the location and zip code of where the transaction occurred. However, this part is not utilized to answer our research question.

[6]Although credit-card bill payments are included.

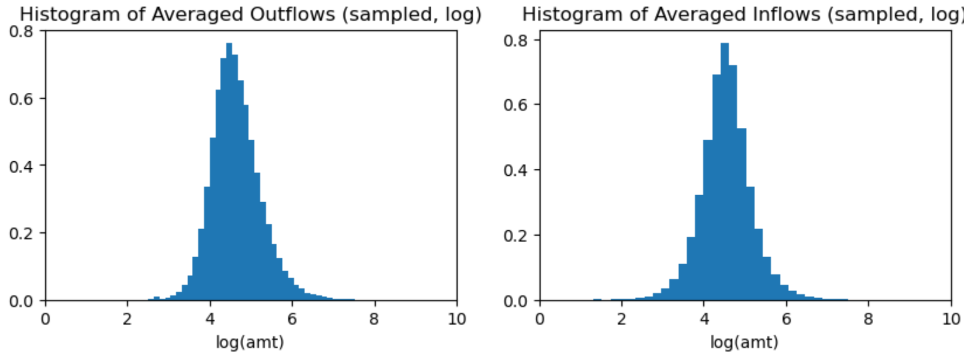

Figure 2: Histograms of monthly averaged outflows (left) and inflows (right) of one million sampled individuals. The averages are over April - December 2021. The count is as a proportion to the total sample size. Only active recipients and non-recipients with no missing characteristic data are included. Profiles with zero inflows or outflows are dropped from the plots.

4 Fiscal Transfers

We find a few fiscal transfer programs in the 18 months between July 2020 and December 2021 that can be tracked from the dataset. They can be grouped into two categories: recurring transfers and COVID-specific transfers[7].

4.1 Identification

The data contains two transaction purposes that are relevant to identifying fiscal transfers: 'elderly welfare' and 'general government welfare.' We find that the purposes themselves, especially the 'general government welfare' tag, are not comprehensive and do not cover every direct fiscal transfers. Therefore, we use these two identifiers to observe transfer patterns in order to identify more direct fiscal transfers. We find that the transfers from these two purposes were made in bulk at midnight and that the transfers originate from a concentrated number of accounts with industry code either in 'general government' or

[7] We want to note that the our dataset does not include transfers to the government welfare card which cover roughly 20 million individuals as of 2020. The government welfare card covers a range of programs for lower-income households and acts as an e-wallet which can be used for spending on essential items and public transport and receiving discounts for utilities and goods at participating stores.

'local government' categories. We leverage this information and tag all transfers made from government related entities to individuals that are made at midnight in bulk as direct fiscal transfers.

4.2 Recurring Transfers

4.2.1 Old Age Allowance (OAA)

The OAA is a non-contributory social pension program that provides monthly financial support to the elderly. Since 2009, the program has been expanded into a universal social pension for all citizens over 60 years of age[8]. The allowance has been adjusted several times and, in 2021, it is incremental based on age: 600 THB, 700 THB, 800 THB, and 1000 THB for participants who are 60-69, 70-79, 80-89, and over 90 years old, respectively. In the fiscal year 2021, the Thai Government reported to having spent 66 Billion THB for the program covering roughly 8 million participants[9].

There are two means of receiving the allowance. The first way is for the recipients to physically receive cash at their local government offices. This option would be observed in the dataset as one large transfer from the Comptroller General's Department account to local government office accounts, leaving us with no further way to track the individual recipients' profiles. The other way is for the recipients to receive the cash transfer from the Comptroller General's Department account directly to their registered bank accounts. The latter option allows us to investigate participants' profiles such as occupation, age, and self-reported income. On average, we find 2.4 million recipients in our dataset each month from July 2020 to December 2021.

Figure 3 shows ages, which is the main program requirement, of the program recipients. Almost all recipients are older than 60 years old, consistent with the age requirement. In addition, the incremental amounts of allowances are accurately transferred to recipients of corresponding ages. Despite the seemingly accurate transfer to the OAA recipients, there are some individuals whose ages are not qualify for the program but still receive

[8]As of 2021; as long as they are not already entitled to pensions from the government; this technically excludes retired government officers and state-owned-enterprises (SOE) officers.

[9]According to the Government Public Relations Department.

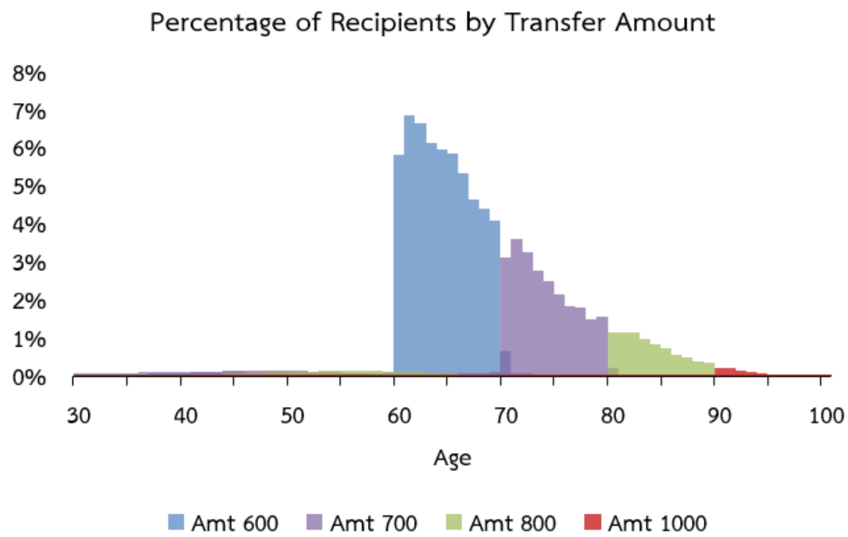

Figure 3: Ages of participants in the OAA in December 2021. Only ages from 30 to 100 years old are shown.

the allowance every month. An explanation could be that these recipients are delegates for their qualified family members and have the allowances transferred into their bank accounts. The delegation is possible and common in recipients who are physically dependent on their younger family members.

4.2.2 Disability Allowance (DA) and Child Support Grant (CSG)

The other two recurring programs in the dataset are the DA and the CSG. These two non-contributory social pension programs are mostly tagged as 'general government welfare' in their transaction purpose field. The DA targets any registered Thai citizen with disabilities, regardless of age. Those under 18 years old are entitled to cash transfer of 1,000[10] THB and those who are 18 and over are entitled to 800 THB a month. The CSG supports 600 THB a month to registered families with a child under six years old and having annual household income below 100,000 THB[11]. Similar to the OAA, qualified persons or families can receive either cash from their local government offices or direct transfer to registered bank accounts of targeted persons themselves or of their legal guardians. In the fiscal year

[10] Before October 2020, those under 18 years old are entitled to 800 THB a month.

[11] The requirement was updated and adopted in 2020.

2021, the government reported that the DA and the CSG had benefited roughly 1.9 and 2.1 million registered individuals, respectively[12].

On average, we find 1.2 million combined recipients for the two programs in our dataset each month from July 2020 – December 2021. Ages of recipients to both programs are consistent with their age qualifications (Figure 4). Ages of the DA recipients, receiving 800 THB, span from 20 to 90 years old, while a few who receive 1,000 THB should be the parents of disable individuals under the age of 18, with profile age being around 40 years old. As for the CSG recipients, they are younger, mostly 20-40 years old, corresponding to age of the parents with children under six years old.

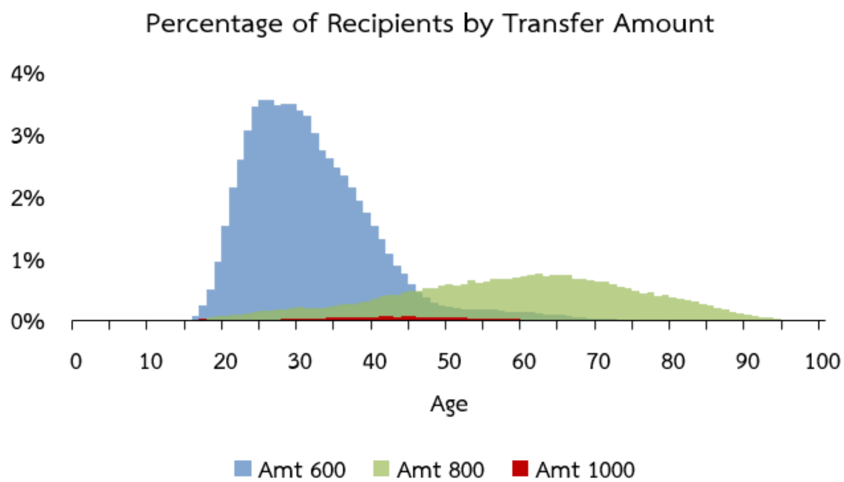

Figure 4: Ages of participants in the DA (amount 800 and 1,000 THB) and the CSG (amount 600 THB) in December 2021. Only ages from 0 to 100 years old are shown.

4.3 COVID-specific Transfers

4.3.1 Transfers in 2020

The first set of transfers in response to the COVID pandemic occurred just before the start of our dataset in April, May, and June 2020. However, there are some people who missed out receiving the transfer during the regular window and ended up receiving the transfers in July and August.

[12]According to news outlets: Isra News and Khaosod.

4.3.2 Transfers in 2021

Two additional measures were implemented in August 2021 to aid formal and informal workers in certain sectors[13] who resided in the lock-down area. The first measure financially supported formal workers under Social Security Act's Section 33 (company employees) who resided in the strict controlled areas[14]. In addition to receiving half of their regular salaries as a compensation, workers under Section 33 would also get an additional 2,500 THB. The second measure financially benefited informal workers under Social Security Act's Section 39 (former company employees who still contribute to the Social Security Fund) and Section 40 (self-employed workers) who resided in the strict controlled areas by providing them with 5,000 THB a month. Qualified workers who resided in the first set of the strict controlled areas received the transfer for two months. These transfers appear in our dataset as either 2,500 THB twice[15] for Section 33 workers or 5,000 THB twice[16] for Section 39 and 40 workers. For those residing in the second set of the controlled areas, participants received either a transfer of 2,500 THB for Section 33 workers or a transfer of 5,000 THB for Section 39 and 40 workers (only once). There are reportedly 3.8 and 8.6 million workers benefited from the first and the second measures respectively[17].

Our dataset is able to capture 2.9 and 5.7 million recipients to Section 33 and Sections 39 and 40, respectively, equivalent to 32.5 and 71.2 billion THB in terms of the transfer amount to individual recipients. Recipients are well targeted as 79% of the recipients have the qualified occupations in their bank profile information, which are employees, self-

[13]Must be in one of the following nine sectors: (i) construction, (ii) accommodation and food service activities, (iii) arts, entertainment and recreation, (iv) other service activities, (v) wholesale and retail trade (repair of motor vehicles and motorcycles), (vi) transportation and storage, (vii) administrative and support service activities, (viii) professional, scientific and technical activities, and (ix) information and communication.

[14]The first set of the strict controlled area includes Bangkok, Nakhon Pathom, Nonthaburi, Pathum Thani, Samut Prakan, Samut Sakhon, Yala, Pattani, Narathiwat, Songkhla, Chachoengsao, Chonburi, Ayutthata (13 provinces). The second set includes Ang Thong, Nakhon Nayok, Nakhon Ratchasima, Kanchanaburi, Lop Buri, Phetchabun, Phetchaburi, Prachuap Khiri Khan, Prachin Buri, Ratchaburi, Rayong, Samut Songkhram, Saraburi, Sing Buri, Suphan Buri, and Tak (16 provinces).

[15]Or 5,000 THB in one month in the case of late registrations.

[16]Or 10,000 THB in one month in the case of late registrations.

[17]https://www.thaigov.go.th/news/contents/details/61310

employed, and business owners, representing workers under Section 33, Section 39, and Section 40 (Figure 5). There are still recipients with unqualified occupations, possibly due to outdated bank account information. Additionally, 64% of the beneficiaries are low income individuals, reporting to earn less than 15,000 a month.

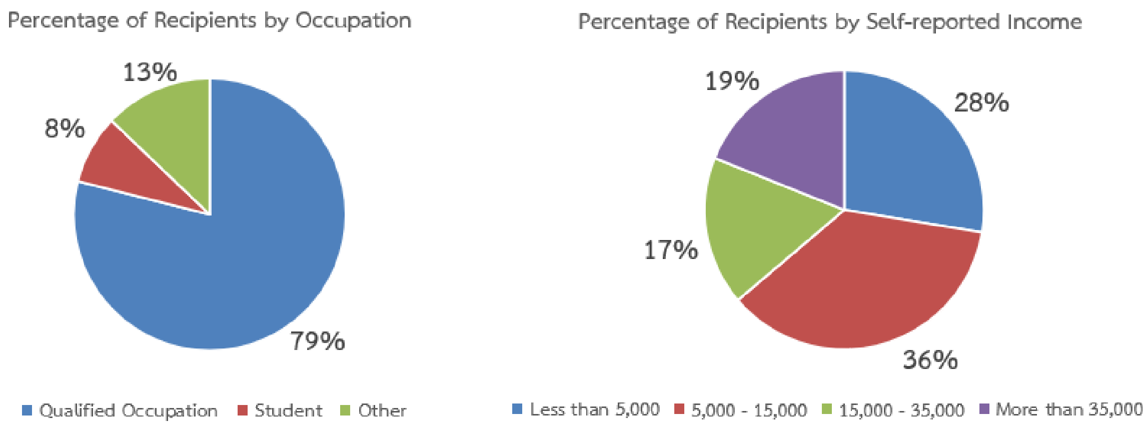

Figure 5: The counts of occupation (left) and self-reported income (right) as a percentage of total recipients. "Qualified occupation" includes employee, self-employed, and business owner. "Other" includes government officer, SOE officer, retired, unemployed, and self-reported other occupation. Self-reported income is in THB per month.

5 Analysis using data at monthly frequency

In this section, we study whether the fiscal transfers have positive impacts on the recipients' spending. Specifically, we focus only on the largest COVID-specific transfers that target workers under Section 39 and Section 40 in either August or September 2021, which covered 75% of the total COVID-specific transfer amount to individuals in those two months. We address this question by quantifying the observed expenditures of recipients during the transfer into two parts: the portion that would have happened without government intervention and the portion that happened because of it. Two estimation methods are implemented: panel ordinary least squares regression and matched observational study.

5.1 Recipients and non-recipients

Let us first define the population samples that we use in the analysis. We define "recipient" as individuals who receive at least one transfer from this specific fiscal program and "non-recipient" as those who never receive any fiscal transfer, regardless of the program, during the 18 months in the dataset[18]. Our sample contains 5.7 million individual recipients and 24.0 million non-recipients.

For data preparation, we perform the following steps prior to the analysis. First, only "active" individuals who made at least two outbound transfers every month in 2021 are included in the analysis. Second, any individuals with missing data on gender, occupation, self-reported income, and age are excluded from the analysis with some exceptions: (i) those with missing income whose occupations are either "unemployed" or "student" are included in the analysis as having zero income and (ii) those with missing occupation are included in the analysis as having occupation "other". Additionally, all included individuals must be over 15 but not older than 100 years old in 2021. Moreover, given that expenditures distinctly spike in March and December of 2021, we only focus on transactions that occur in April through November 2021. Lastly, we keep only recipients whose total spendings over that period are below the 90^{th} percentile to account for highly right-skewed spending distribution. The original 5.7 million individual recipients (and 24.0 million non-recipients) whom we have profile information on are reduced to 2.2 million recipients (and 11.8 million non-recipients) for the analysis.

5.2 Research Question

Our main research objective is to quantify the impacts of the fiscal transfers. Here, we further refine it into two questions. The first being how the transfers affect spending. The answer to this question would tell us whether the program implementation generated a desirable positive impact on the economy and how it could be improved to achieve a better outcome given the fiscal resource scarcity. The second question is whether the transfers compensate for lost expenditures during lockdowns. This would help us evaluate

[18] To ensure that any patterns we extract from the non-recipient data are not influenced by any additional income from the government.

the effectiveness of the program in terms of the total impacts of both lockdowns and transfers.

5.3 Question 1: Panel Ordinary Least Squares Regression

We perform panel ordinary least squares regressions with the following specification, using recipients' data:

$$Y_{i,t} = \alpha + \beta * Baseline_i + \gamma * Dummy_{i,t} + \delta * char_i + \theta * nonrecipient\_spending_t + \epsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ represents the amount that recipient i spends in month t. $Baseline_i$ is the amount recipient i spends in January 2021 to capture a recipient's baseline level of spending. $Dummy_{i,t}$ is a 0 or 1 dummy that indicates whether recipient i has received fiscal transfer in or prior to month t. $char_i$ is the individual-specific characteristics, which are gender, age group, occupation, and the log of the self-reported income. $nonrecipient\_spending_t$ is the non-recipients' monthly median spending in month t.

The regression result of Equation 1 is shown as Model 1 in Table 1. A recipient spends 2470 THB, on average, more each month once they receive the fiscal transfer compared to the months prior to the transfer. Moreover, highest spending is associated with being in the age group between 25 and 40 years old, the prime-working age group which is likely to spend more to provide for their families. Business owners spend the most among all occupations, followed by retirees. Students are the lowest spenders. The significance of the results on *Dummy* and *occupation* are confirmed by Model 2, which excludes *Baseline*. Further robustness checks (Table A1) show that these results hold even in the full sample where the spending above 90^{th} percentiles are included. However, the coefficient on gender is not as robust, given that the sign of the coefficient changes from positive to negative in alternative specifications.

5.4 Question 1: Matched Observational Study

The spending behaviors of non-recipients ideally could provide us with more information as a counter-factual; how a recipient behaves had he/she not received the fiscal arrangement

	Model 1		Model 2	
$Y_{i,t}$: **Monthly spending**	Coefficient	Standard Error	Coefficient	Standard Error
Fiscal Dummy	2470***	(50.44)	2492***	(50.69)
Baseline	0.02***	(0.00)		
Non-recipient Spending	1.21***	(0.01)	1.2***	(0.01)
Income (log)	2939***	(8.54)	3025***	(8.58)
Gender - male	-2028***	(34.10)	-2052***	(34.27)
Occupation				
Business owner	17850***	(294.9)	18224***	(296.36)
Employee	-3743***	(294.55)	-3851***	(296.02)
Government officer	-3283***	(346.84)	-3419***	(348.56)
Retired	6360***	(580.23)	7001***	(583.12)
Self-employed	-786**	(293.82)	-878***	(295.29)
Student	-6612***	(299.45)	-6802***	(300.93)
Unemployed	2837***	(300.40)	2902***	(301.89)
Other	-133	(302.47)	-143	(303.98)
Age				
(25, 40]	11331***	(47.56)	11601***	(47.79)
(40, 50]	7817***	(48.46)	8003***	(48.70)
(50,60]	3466***	(56.98)	3597***	(57.26)
(60, 100]	-1557***	(135.65)	-1363***	(136.32)
Constant	-19832***	(431.45)	-19491***	(433.59)
Adjusted R^2	0.05		0.04	
Observations	2247808		2247808	

Table 1: Panel ordinary least squares regression results of Model 1 (Equation 1) and Model 2 (without *Baseline*). Occupation SOE officer, gender female, and age group (15-25] are used as basis values in the regressions. The symbol $*$, $**$, and $***$ indicate the significance level at 10%, 5%, and 1%, respectively.

while leaving everything else the same. However, without a randomized controlled experiment, recipients and non-recipients may possess different features other than receiving and not receiving the transfer. This fact prevents us from directly comparing them without suffering from bias. Matched observational study provides one approach that is used in many studies to handle such a problem. Guo et al. (2020) discussed several matching methods to reduce the bias including nearest neighbor with caliper and Mahalanobis distance matching.

Opting for this approach, we match the treatment group (recipients) to a subset of the control group (non-recipients), by following ideas in Rosenbaum (2010) and Rosenbaum (2020). We use a combination of a nearest neighbor model of the Mahalanobis distance and a caliper on the logistic propensity score of the likelihood of being in the treatment group. The Mahalanobis distance and the logistic propensity score are based on the following features: age, the log of the self-reported income, and monthly spending prior to the month of interest. A caliper is also used enhance the matching result, with the cutoff set to 0.2 as suggested in Cochran & Rubin (1973).

We approach the first question by inspecting how a recipient and a non-recipient with similar characteristics and pre-transfer spending patterns behave differently after the first transfers occur in August 2021. That is, using the full sample from the panel OLS exercise (2.5 million recipients and 11.8 million non recipients), we match the treatment and the control groups based on the following features: occupation[19], the log of self-reported income, age, and their monthly spending between April and July 2021. Figure 6 shows that distributions for different characteristics of the control group become more similar to those of the treatment group.

The matched sample is segmented into four groups depending on the percentile of the treatment's self-reported income: (i) below the 25^{th} percentile, (ii) between the 25^{th} and the 50^{th} percentiles, (iii) between the 50^{th} and the 75^{th} percentiles, and (iv) between the 75^{th} and the 90^{th} percentiles. Additionally, outliers are removed to mitigate the effect of highly right-skewed spending distribution. Outliers are defined here to be those whose spending in any month in the 2021 is over the 90^{th} percentile of that month's spending or their corresponding matches are outliers. Table A3 in the Appendix reports the subsample sizes after the removal of outliers for different cases.

Figure 7 displays monthly spending patterns for each of the self-reported income groups to account for heterogeneity. The expenditures of both the treatment and the control groups are similar during April through July 2021, which is not surprising since we restrict them to be so in the matching process. After the first fiscal transfer in August, the treatment group

[19]We perform multiple but smaller matchings within each of the occupations, as a result, recipients and non-recipients in each matched pair have the same occupation.

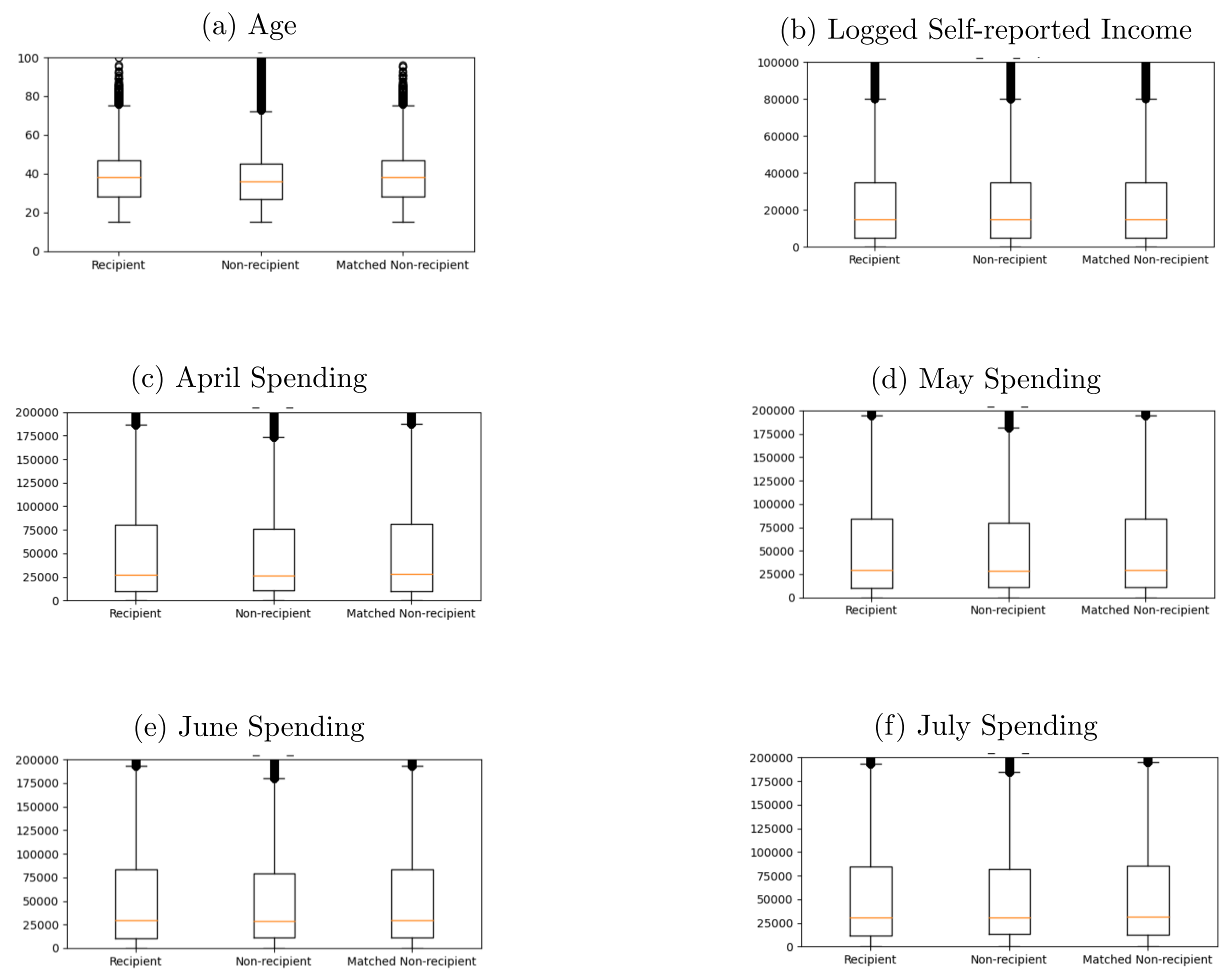

Figure 6: Characteristic distributions of recipients (left), non-recipients (middle), and matched non-recipients (right).

starts to spend slightly more, compared to the control group; this is more noticeable in the groups with lower incomes. For comparison, the marginal per-month median spending after the transfer is 1514 THB, which is comparable in magnitude to the 2470 THB found in Model 1 of the regression.

To further quantify the spending difference between the treatment and control groups, we compute the marginal propensity to consume (MPC) over the periods between August and October 2021. For each treatment, there is a corresponding control who, by the matching process, is supposedly identical to the treatment with one difference: that he/she does not receive the fiscal transfer. Thus, each of the corresponding controls can be thought of as a counter-factual instance of the matched treatment if he/she had not received the transfer. Then, the difference spending between each pair is the marginal spending as a result of the transfer, and the difference divided by the fiscal transfer amount received is defined here to be the MPC[20]. We find that the fiscal transfers result in a spending increase of 49% of the fiscal transfer amount for the overall population and is higher for the groups with lower income (Table 2)[21]. Therefore, to answer the first question, the transfers have positive impacts on the spending and the impact is amplified for the lower income population.

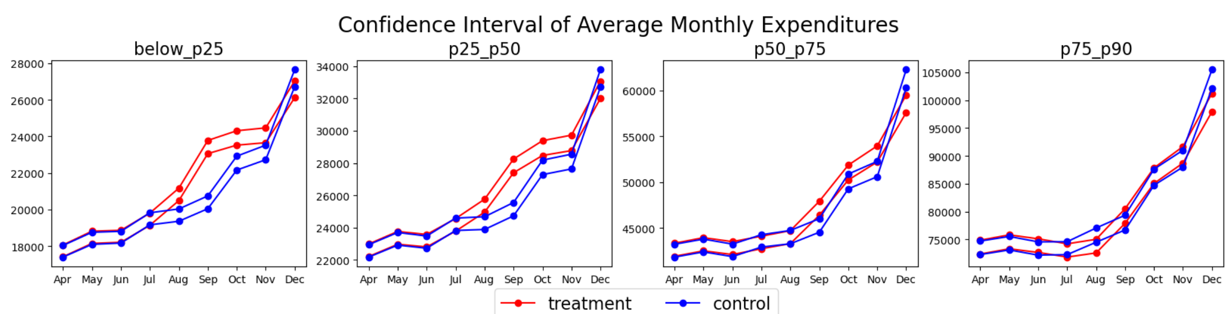

Figure 7: Question 1: the impact of the fiscal transfer. The 90% confidence interval of averaged monthly expenditures of the treatment group (red) and the control group (blue) from April - December 2021, by income groups. The confidence intervals are constructed from 10,000 bootstraps with sample size of 10,000 in each bootstrap.

[20]Without cash withdrawals data, this value could be underestimated.

[21]We find similar results when applying an alternative outlier removal process that considers the total spending in 2021 instead of the monthly spending. See Figure A1 and Table A4 in the Appendix.

Income group	MPC
Below the 25^{th} percentile	0.62*
Between the 25^{th} and 50^{th} percentiles	0.55*
Between the 50^{th} and 75^{th} percentiles	0.27*
Between the 75^{th} and 90^{th} percentiles	-0.08
Overall MPC: Below the 90^{th} percentile	0.49*

Table 2: Question 1: the impact of the fiscal transfer. MPC over August through October 2021, by income groups. The symbol * indicates the significance level of 10%.

5.5 Question 2: Fiscal Transfers as a Compensation Tool for Lost Spending

To inspect whether the transfer compensates for losses in spending during the lockdown, we want to compare the effect of the transfers on a recipient against a non-recipient who behaved similarly prior to the lockdown. We conduct a similar matching analysis by relying on the same demographic characteristics as in the previous exercise and pre-lockdown monthly spending amounts in January - April 2021. Unlike the previous analysis, whether a person is affected directly by the lockdown matters, therefore, we impose an additional restriction on locations so that the treatment group covers only the recipients who work or reside in one of the 29 lockdown provinces and the control groups are non-recipients who do not reside in the lockdown provinces. The matching result ensures that each pair of a recipient and a non-recipient has (i) similar characteristics, (ii) similar spending pattern prior to the lockdown in May 2021, and (iii) recipients are in lockdown areas while non-recipients are not. The difference in spending behavior after May 2021 would, then, reflect the impact of the lockdown and the recovery path afterwards. The additional restriction on location leads to 2 million recipients and 4.3 million non-recipients for the full sample analysis. The same outlier removal process as the previous analysis is repeated. There is 65% out of the 2 million matches remaining in the analysis (Table A3).

Overall, the expenditure of the treatment group starts to drop below the control group's in May and begins to catch back up in the month of the first transfer for some income groups

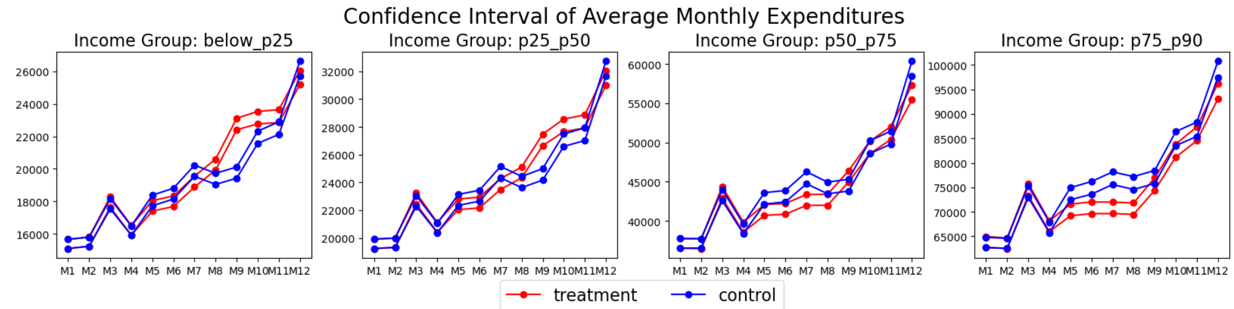

Figure 8: Question 2: fiscal transfers as a compensation tool for lost spending. The 90% confidence interval of averaged monthly expenditures of the treatment group (red) and the control group (blue) from January - December 2021, by income groups. The confidence intervals are constructed from 10,000 bootstraps with sample size of 10,000 in each bootstrap.

(Figure 8). The two lower income groups living in the lockdown area spend significantly less than the control groups by 1,460.8 and 1,619.3 THB (Table 3). During the transfer period in August - October, the individuals in the lockdown area who receive the fiscal transfers spend significantly more than the control groups by 5,075.9 and 4,248.7 THB per month. As a result, the losses in spending in May through July are more than compensated for by the fiscal transfer as the net spending of both income groups are significantly positive over the entire period when compared to the corresponding control groups. On the contrary, the two higher income groups end up not recovering from the lockdown spending loss. The spendings of higher-income individuals in the lockdown areas are significantly less than of the corresponding control groups during the lockdown and by the end of the fiscal program in October despite receiving the fiscal stimulus. That is, only the lower income groups have recovered from the lockdown with higher total spending while it is not the case for the higher income groups.

6 Analysis using data at daily frequency

With the high frequency dataset, we are able to investigate expenditure and inflow patterns on a daily basis. In this section, we are interested in how recipients spend their money, especially on the day of and a few days after the transfer date, and how their spending

Income Group	Apr - Jul	Aug - Oct	Net
Below the 25th percentile	-1460.8*	5,075.9*	3,615.1*
Between the 25th and 50th percentiles	-1,619.3*	4,248.7*	2,629.4*
Between the 50th and 75th percentiles	-5,727.3*	-429.4	-6,156.8*
Between the 75th and 90th percentiles	-13,224.3*	-9160.7*	-22,385.0*

Table 3: Question 2: fiscal transfers as a compensation tool for lost spending. The averaged differences of total expenditures between the treatment and the control groups over April - July 2021, August - October 2021, and the net between the two periods. The symbol * indicates the significance level at 10%. Positive sign means expenditures of the treatment group is higher than of the control group.

patterns are different from those who do not receive the transfers.

To achieve this, we take the 2.5 million treatment-control pairs from the monthly analysis for question 1, where all recipients' first transfers occurred in August or September 2021. We let the first transfer date of each individual be day $t = 0$. The individuals' days $t = 0$ are not necessarily the same calendar date as the transfer dates can vary by 1-3 days within the second halves of the months. The analysis focuses on what happens during 15 days before and after day $t = 0$. We start with the full sample of matched pairs in the monthly analysis, and apply an outlier removal similar to the monthly analysis. That is, outliers are defined as those (including their corresponding matches) who have daily spending over the 97.5th percentile in any day over the 31 day period. There is 63% out of the 2.5 million matches remaining in the analysis (Table A3). The average inflow and outflow of the treatment group are compared against those of the control group and the results are displayed based on self-reported income as in the monthly analysis.

6.1 Daily Inflows during the Transfer Period

Inflow patterns (Figure 9) of the treatment and the control groups are not much different except on the first transfer date and the five days after. The treatment group's daily inflows temporarily spikes to over 7,000 THB on day $t = 0$, while the inflows of the control group gradually increase on the same day with a much smaller size and linger longer for two

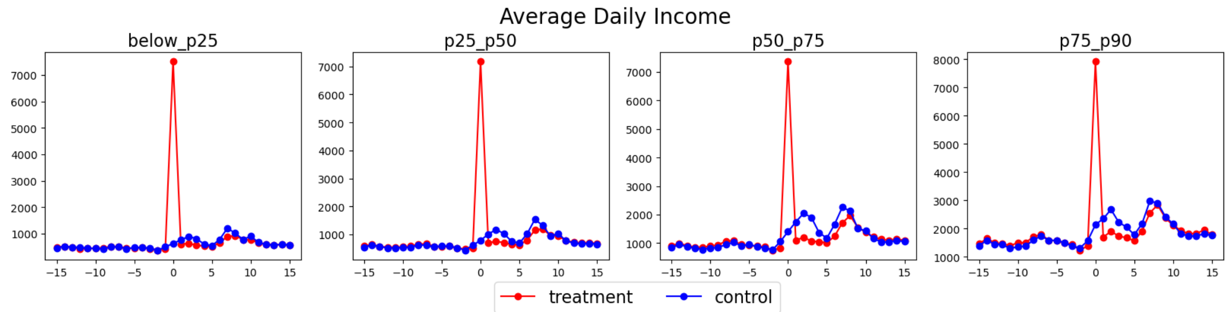

Figure 9: The average monetary inflows over 31 days (15 days prior and after the first government transfer date) of the treatment group (red) and the control group (blue). The averages are of sample means from 10,000 bootstraps with sample size of 10,000 in each bootstrap.

to three days. It is by definition that the government transfer explains the spike on day $t = 0$ for the treatment group. As for the control group, the increase in the days after $t = 0$ could reflect a small circulation of money in the economy that the transfers stimulate before dying down.

After the first decline, both groups' inflow patterns similarly, amount-wise and time-wise, increase again around day $t = 6$ to $t = 10$. It is highly likely that the synchronous inclines in both groups are due to their payrolls since most recipients' first transfer dates are during the 20$^{\text{th}}$ to the 25$^{\text{th}}$ of a month, making day $t = 6$ through $t = 10$ fall around the end of month, which is the monthly payroll period in Thailand. During the payroll period, the treatment groups amongst all income levels receive slightly less income than the corresponding control groups, suggesting a decrease in regular payroll compared to how much the treatment groups would have obtained. No heterogeneity in inflow patterns is observed.

6.2 Daily Expenditures after Transfers

The expenditure patterns in Figure 10 are similar to the inflow graphs in Figure 9. There are two distinct peaks that occur at the same time period as in the inflow pattern. Individuals are likely to spend as soon as they receive the transfers. As a result, we see high peaks on day $t = 0$ when the treatment group receives the transfers and smaller peaks around day

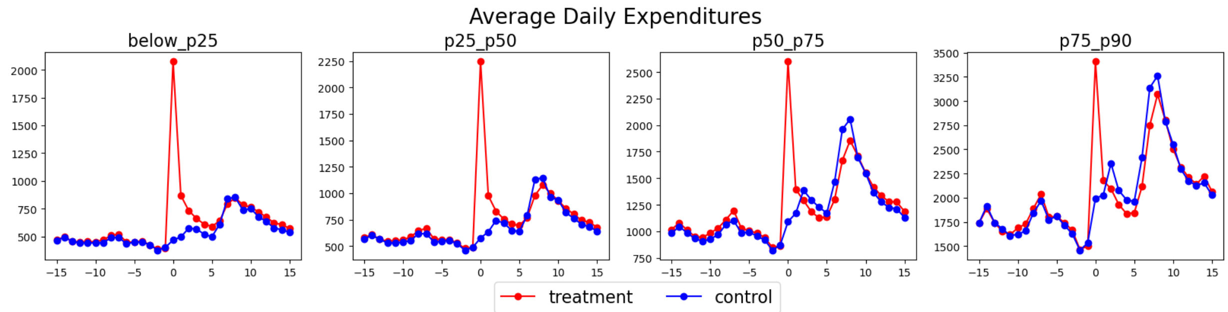

Figure 10: The average monetary outflows over 31 days (15 days prior and after the first government transfer date) of the treatment group (red) and the control group (blue). The averages are of sample means from 10,000 bootstraps with sample size of 10,000 in each bootstrap.

$t = 6$ to day $t = 10$ during the payroll period for both groups. No heterogeneity is observed except for that high self-reported income individuals generally spend more.

6.3 Marginal Propensity to Consume

To quantify the difference in expenditure between the two groups, we now focus on the MPC, defined in the same way as in Section 5.4. As seen in Figure 9 and Figure 10, expenditures during the second peak may be generated not by the fiscal transfer but regular monthly payroll. To account for this, only expenditures from day $t = 0$ to day $t = 5$ are included in the MPC calculation.

Table 4 reports the MPC results[22]. We find that the transfers made in August and September 2021 result in an MPC of 40% overall over the 6 days since the date of the transfers. When considering by income groups, the MPCs are larger for low self-reported income individuals. The transfers generate more spending by 44% of the transfer amount for individuals with self-reported income below the 25$^{\text{th}}$ percentile. The number decreases as the self-reported income increases. As for the individuals between the 75$^{\text{th}}$ and 90$^{\text{th}}$ percentiles of income, the spending that the transfers generate increase by only 16% of the transfer amount.

[22] We find a similar result when removing outliers based on the total spending over the 31 day period. See Table A6.

Income Group	MPC
Below the 25$^{\text{th}}$ percentile	0.44*
Between the 25$^{\text{th}}$ and 50$^{\text{th}}$ percentiles	0.42*
Between the 50$^{\text{th}}$ and 75$^{\text{th}}$ percentiles	0.26*
Between the 75$^{\text{th}}$ and 90$^{\text{th}}$ percentiles	0.16*
Overall MPC: Below the 90$^{\text{th}}$ percentile	0.40*

Table 4: MPC over day $t = 0$ to day $t = 5$ by income group, with outlier pairs removed. The symbol * indicates the significance level of 10%. Outliers are considered based on their daily spending.

7 Conclusion

This paper examines the impacts of COVID-19 fiscal transfers using a rich transaction dataset. We first document the profiles of the recipients, which were in line with the groups targeted by the government; before specifically looking at an event study for the COVID-specific transfers made in 2021. For this event study, we find that total marginal propensity to consume (in our case, spend) to be 49% of the amount transferred. However, the impacts of the transfers were heterogeneous. The spending of lower-income individuals statistically rose after the transfers, with marginal propensity to consume (spend) of up to 62% of the value received from the transfers. We also observe that these lower-income individuals who lived through the lockdown and received fiscal transfers spend more on aggregate than similar individuals that didn't live in lockdown areas and, therefore, did not receive government support. On the other hand, we find no statistical evidence that higher income individuals spend more after the transfer and their aggregate spending is much lower than those individuals living in non-lockdown areas who did not receive government support.

At the daily level, we find that most individuals spend the money in the day of the transfers or the days immediately after receiving them. This is an interesting finding but will require further analysis to fully explain.

The paper adds to the empirical literature on the impacts of direct fiscal transfers to households and the heterogeneous impacts fiscal transfers can have. The results also substantiate the development of economic models that take into account the heterogeneity in consumption patterns based on income levels.

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A Robustness

This section includes supplementary estimations as robustness exercises for the analyses in Section 5 and Section 6.

A.1 The Variations of Panel OLS specifications

We perform four additional estimations with different specifications and/or on different subsamples to substantiate the results of the two main estimations in Section 5.3. Tables A1 and A2 report the supplementary results. Model 3 and Model 4 have the same specification as Model 1 and Model 2, respectively, but are estimated on the full sample. Model 5 and Model 6 use the ratio of monthly spending over their January 2021 spending as a dependent variable, instead of monthly expenditure as in the previous models. The *Trend* variable in the *ratio* estimations is correspondingly changed to the monthly median of non recipients' ratio. Similarly to the main estimations, occupation SOE officer, gender female, and age group (15-25] are used as basis values in the regressions.

The positive impact of the fiscal transfer is supported by the positive coefficients of *Dummy* in Model 3 and Model 4, although being twice as much. However, the *ratio* models (Model 5 and Model 6) do not report significant results for any variable.

A.2 An Alternative Outlier Removal Process

In addition to the outlier removal method in Section 5 and Section 6, we perform a more relax, alternative approach where outliers are determined as observations whose total spending over 2021 for the monthly analysis and over the 31 day period for the daily analysis is greater than the 90^{th} percentile. Observations are still considered as outliers if their corresponding matches are one. Table A3 reports the remaining observations as a percentage of the full sample.

Matched to address the first question (Section 5.4), monthly spendings and incomes are displayed in Figure A1. Similar to the main estimation, the treatment group starts to spend more in August, where the lower income group spends relatively more when compared to their corresponding matches. Moreover, both groups behave more similarly in

	Model 3		Model 4	
$Y_{i,t}$: **Monthly spending**	Coefficient	Standard Error	Coefficient	Standard Error
Fiscal Dummy	4594^{***}	(749)	6148^{***}	(820)
Baseline	0.57^{***}	(0.00)		
Non-recipient Spending	2.99^{***}	(0.16)	2.74^{***}	(0.18)
Income (log)	10966^{***}	(128)	20659^{***}	(141)
Gender - male	3289^{***}	(506)	5595^{***}	(555)
Occupation				
Business owner	89249^{***}	(4435)	155898^{***}	(4856)
Employee	12261^{**}	(4435)	16069^{***}	(4856)
Government officer	5951	(5230)	6227	(5727)
Retired	47637^{***}	(8403)	119791^{***}	(9201)
Self-employed	23044^{***}	(4424)	28275^{***}	(4844)
Student	30107^{***}	(4512)	50534^{***}	(4940)
Unemployed	47065^{***}	(4522)	74544^{***}	(4952)
Other	23940^{***}	(4553)	39577^{***}	(4985)
Age				
(25, 40]	4435^{***}	(708)	18810^{***}	(776)
(40, 50]	-3998^{***}	(722)	7804^{***}	(790)
(50,60]	-15344^{***}	(848)	-7424^{***}	(928)
(60, 100]	-19501^{***}	(2008)	-1759	(2199)
Constant	-157927^{***}	(6452)	-208204^{***}	(7064)
Adjusted R^2	0.169		0.004	
Observations	2497565		2497565	

Table A1: Panel ordinary least squares regression results of supplementary estimations of monthly spending amount on the full sample. Occupation SOE officer, gender female, and age group (15-25] are used as basis values in the regressions. The symbol $*$, $**$, and $***$ indicate the significance level at 10%, 5%, and 1%, respectively.

November onward. As for the MPC, the transfers have positive impacts on the two lower income groups, with the MPCs at 55% and 47% (Table A4). However, there is not enough evidence of this finding when looking at the overall population.

Figure A2 and Table A5 report the robustness exercises to address the second question of the monthly analysis. The essence of the results is in line with the main findings. However, there is not enough evidence that the lower income groups are compensated more

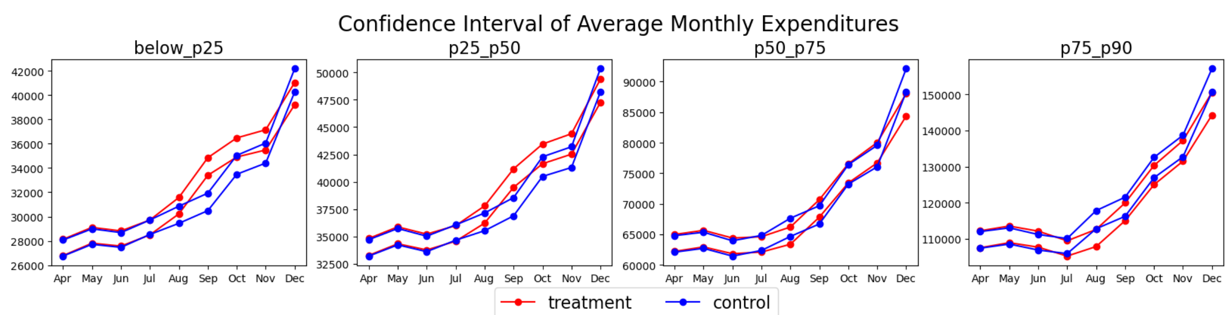
	Model 5		Model 6	
$Y_{i,t}$: **Monthly ratio**	Coefficient	Standard Error	Coefficient	Standard Error
Fiscal Dummy	2.21	(2.85)	-7.01	(6.82)
Non-recipient Spending	19.74	(15.42)	40.31	(36.91)
Income (log)	0.21	(0.51)	-0.65	(1.24)
Gender - male	-2.99	(2.04)	9.2^{*}	(4.88)
Occupation				
Business owner	1.77	(17.61)	0.61	(42.7)
Employee	3.1	(17.59)	1.6	(42.7)
Government officer	0.64	(20.71)	-0.95	(50.35)
Retired	4.71	(34.64)	6.75	(80.9)
Self-employed	3.51	(17.54)	15.81	(42.59)
Student	2.04	(17.88)	2.34	(43.44)
Unemployed	2.72	(17.94)	2.39	(43.54)
Other	41.99^{**}	(18.06)	36.71	(43.83)
Age				
(25, 40]	3.14	(2.84)	2.3	(6.82)
(40, 50]	-4.01	(2.89)	13.01^{*}	(6.95)
(50,60]	-4.12	(3.4)	-4.85	(8.16)
(60, 100]	-4.73	(8.1)	-4.52	(19.33)
Constant	-21.97	(25.1)	-40.15	(60.55)
Adjusted R^2	0.00		0.00	
Observations	2247808		2497565	

Table A2: Panel ordinary least squares regression results of supplementary estimations of monthly ratio on the sub sample (Model 5) and the full sample (Model 6). Occupation SOE officer, gender female, and age group (15-25] are used as basis values in the regressions. The symbol $*$, $**$, and $***$ indicate the significance level at 10%, 5%, and 1%, respectively.

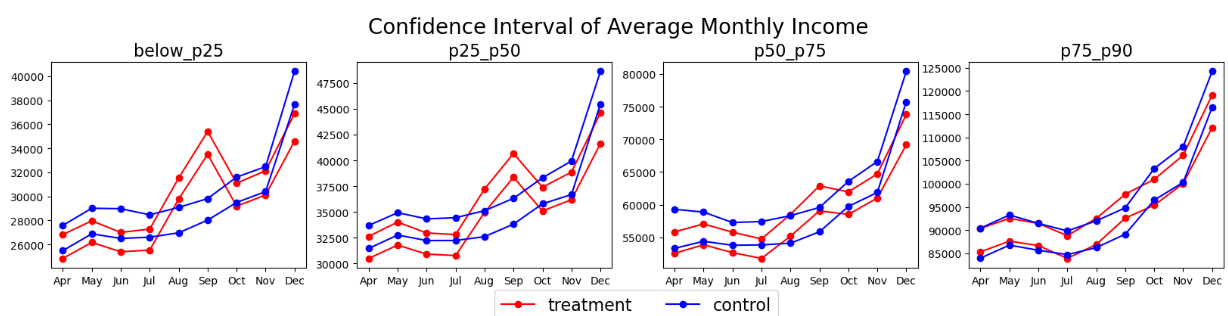
than they have lost, while the higher income groups still do not fully recover from the lockdown. For the robustness exercise of the daily analysis, the spending patterns (Figure A3) suggest similar messages as the main findings, and the MPC estimation (Table A6) are still positive for the overall and the lower income groups.

	Main	Appendix (Robustness)
Monthly (1st question)	70%	89%
Monthly (2nd question)	65%	88%
Daily	63%	86%

Table A3: The percentage of the remaining matches. All analyses use the 90th percentile as a threshold, except for the main daily analysis, which uses the 97.5th percentile, to ensure that the sub sample size is more than 60% of the full sample.



(a) Averaged monthly expenditures

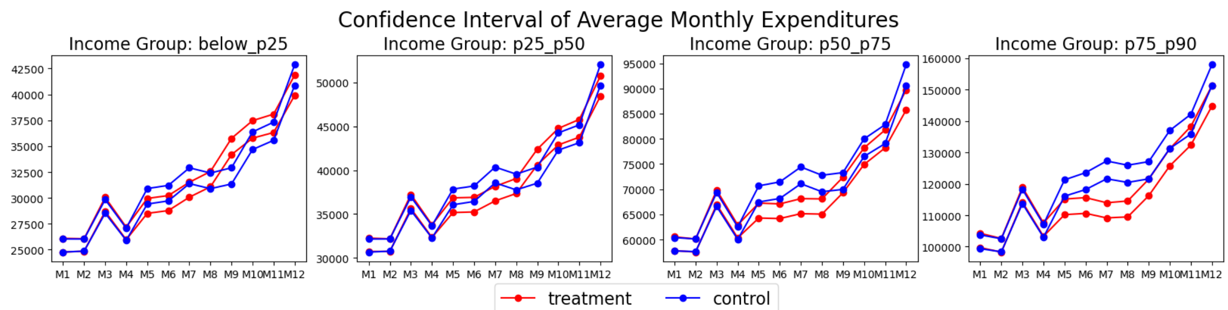


(b) Averaged monthly incomes

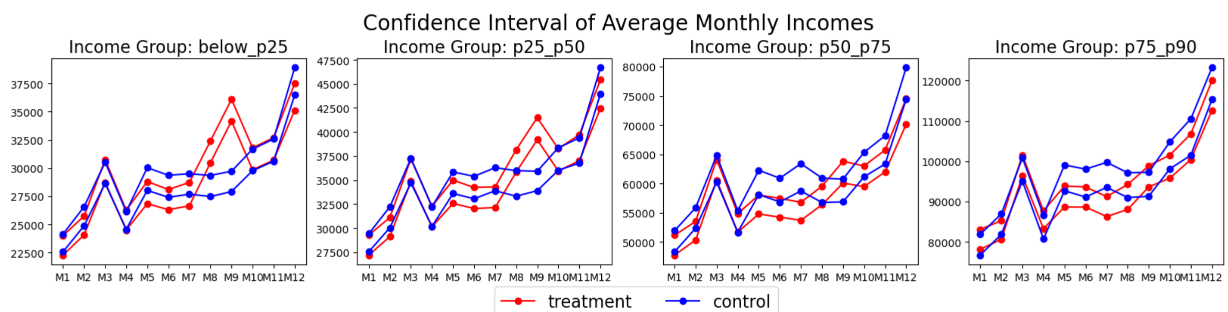
Figure A1: The 90% confidence intervals of averaged monthly expenditures (top) and incomes (bottom) of the treatment group (red) and the control group (blue) from April - December 2021, by income groups. An alternative where outliers are considered based on the total spending in 2021 is used. The confidence intervals are constructed from 10,000 bootstraps with sample size of 10,000 in each bootstrap.

Income group	MPC
Below the 25th percentile	0.55*
Between the 25th and 50th percentiles	0.47*
Between the 50th and 75th percentiles	-0.10
Between the 75th and 90th percentiles	-1.06*
Overall MPC: Below the 90th percentile	0.24

Table A4: MPC over August, September, and October 2021 by income groups. The symbol * indicates the significance level of 10%. An alternative where outliers are considered based on the total monthly spending of all 12 months in 2021.



(a) Averaged monthly expenditures

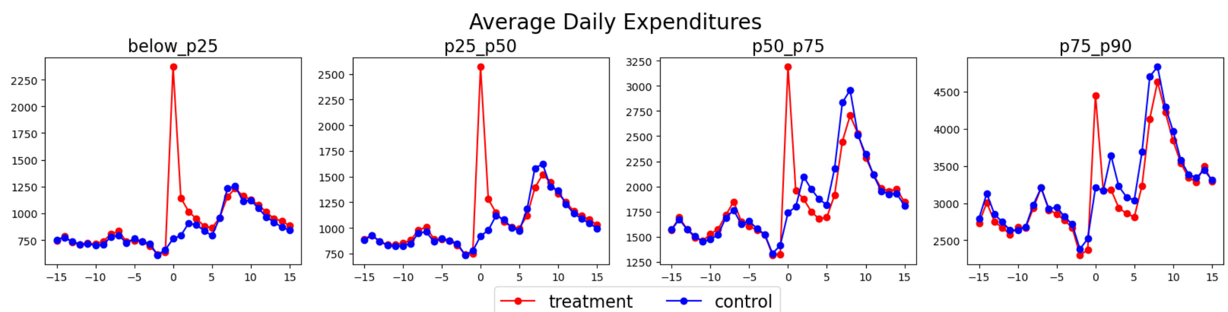


(b) Averaged monthly incomes

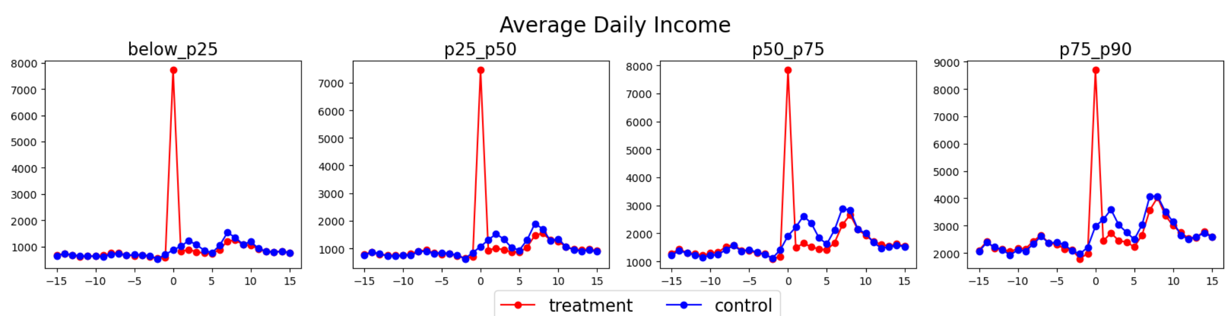
Figure A2: The 90% confidence intervals of averaged monthly expenditures (top) and incomes (bottom) of the treatment group (red) and the control group (blue) from January - December 2021, by income groups. An alternative where outliers are considered based on the total spending in 2021 is used. The confidence intervals are constructed from 10,000 bootstraps with sample size of 10,000 in each bootstrap.

Income Group	Apr - Jul	Aug - Oct	Net
Below the 25th percentile	-3,154.6*	4,084.3*	929.7
Between the 25th and 50th percentiles	-4,225.3*	2,140.9	-2,084.4
Between the 50th and 75th percentiles	-13,216.9*	-7,067.8*	-20,284.7*
Between the 75th and 90th percentiles	-26,195.3*	-22,386.8*	-48,582.1*

Table A5: The averaged differences of total expenditures between the treatment and the control groups over April - July 2021, August - October 2021, and the net between the two periods. The symbol * indicates the significance level at 10%. Positive sign means expenditures of the treatment group is higher than of the control group. An alternative where outliers are considered based on the total spending in 2021 is used



(a) Averaged daily expenditures



(b) Averaged daily incomes

Figure A3: The averaged daily expenditures (top) and incomes (bottom) over 31 days (15 days prior and after the first government transfer date) of the treatment group (red) and the control group (blue). An alternative approach where outliers are considered based on the total spending over the 31 days is used. The averages are of sample means from 10,000 bootstraps with sample size of 10,000 in each bootstrap.

Income Group	MPC
Below the 25^{th} percentile	0.41*
Between the 25^{th} and 50^{th} percentiles	0.37*
Between the 50^{th} and 75^{th} percentiles	0.15*
Between the 75^{th} and 90^{th} percentiles	-0.01
Overall MPC: Below the 90^{th} percentile	0.31*

Table A6: MPC over day $t = 0$ to day $t = 5$ by income group, with outlier pairs removed. The symbol * indicates the significance level of 10%. An alternative where outliers are considered based on the total spending over the 31 day period.

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