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Do CashlPess Payments Stimulate Spending? Evidence from QR Code Payment Campaigns and Bank Transaction Data in Japan

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Do Cashless Payments Stimulate Spending? Evidence from QR Code Payment Campaigns and Bank Transaction Data in Japan

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Abstract

This study examines whether cashless spending stimulates spending through subdued salience. We use bank transaction data and leverage events related to Quick Response (QR) code campaign as an instrumental variable. Our estimation offers supporting evidence for subdued salience, demonstrating that an increase in QR code payments prompted by campaigns leads to an approximately same-sized increase in other spending. However, this effect is transitory. Nevertheless, the effect of QR code campaigns on QR usage exerts a lasting impact over time, increasing the fraction of QR code users by a minimum of 1%.

JEL Classification Number: D12, E42, E21, G51

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†Waseda University (E-mail: kozo.ueda@waseda.jp). The data were made available through a strict contract between Mizuho Bank and Waseda University, and were analyzed in a setting in which measures such as masking and other anonymous processing were taken to prevent the identification of individuals. The authors would like to thank the staff of Mizuho Bank, Shin Kikuchi, and seminar participants at Meiji University. Ueda is grateful for the financial support from the JSPS (19H01491, 23K17562, 23H00046). The views and opinions expressed in this paper are solely those of the authors and do not reflect those of Mizuho Bank.

1 Introduction

As cashless (electric) payments continue to proliferate globally, concerns have arisen regarding their potential to stimulate overspending (e.g., BBC 2019). One source of such concern is that cashless payments are less salient transactions than cash payments (e.g., Agarwal et al. 2022).[1] Cashless payments may diminish consumers' awareness of their daily expenditure, subduing salience (Agarwal et al. 2022). However, the possibility exists that cashless payments decrease spending by reducing transaction and monitoring costs (e.g., Bachas et al. 2021). In terms of the latter, cashless payments allow users to maintain comprehensive transaction records, so that they can review their transaction history. This enhanced monitoring may foster trust in banks and also help them to optimize their spending, especially when coupled with household account book apps. Studying the effects of cashless payments holds implications not only for household finance but also for money demand and potential consequences of adopting cryptocurrencies or central bank digital currency (CBDC) in the foreseeable future.

In this study, we aim to investigate the causal effects of cashless payments on consumer spending. Accordingly, we use novel bank transaction data in conjunction with the occurrence of cashless payment campaigns in Japan. Specifically, we focus on a particular type of cashless payments, a Quick Response (QR) code payment, wherein individuals use a payment app on their smartphones or compatible devices to scan a two-dimensional barcode displayed by a merchant (or a merchant scans a code on users' devices) to process a transaction. Notably, PayPay, the predominant player in QR code payments in Japan, launched extensive campaigns in collaboration with local governments spanning from July 2020 to February 2021. During these campaigns, users were eligible to receive rebates of around 20–30% upon making payments via PayPay at designated merchants within designated regions. Crucially, the timing and geographic coverage of these campaigns were exogenous to users, thereby exhibiting temporal and regional variations. We leverage campaign information as an instrumental variable (IV) to estimate the causal effects of QR code payments on spending. This information is complemented with bank transaction data provided by a mega bank in Japan. At the individual and weekly levels, we analyze how individuals' spending change in response to QR code payments, where

[1] Studies have also highlighted that cashless payments influence spending by reducing transaction costs (e.g., Jack and Suri 2014) or alleviating liquidity constraints (e.g., Buy Now, Pay Later (BNPL) platforms, see Di Maggio, Katz, and Williams 2022).

an IV takes the value of one if an individual lives in a region where QR code campaigns are underway during a given week.

The secondary, yet significant, contribution of this study is that it documents the effectiveness of campaigns on cashless payments. A comparison between individuals residing in regions targeted by the PayPay campaigns and those outside the campaign areas reveals a discernible increase in the proportion of QR code users. Specifically, the campaigns increased the fraction of QR code users, that is, those who transfer money from their bank accounts to their QR code accounts, by a minimum of 0.9% in the total population. Furthermore, this campaign effect persists over the long term: even 16 months post-campaign cessation, the disparity in the fraction of QR code users remains at 0.9%. This finding implies the presence of switching costs of changing payment method and benefits of using QR code payments. It is worth noting that our estimation of this effect size is conservative, as other forms of QR code payments, such as those involving cash and credit cards, are not encompassed in our dataset and QR code users in the neighboring regions can go shopping in the region under a campaign, which is not included in our estimation.

The following results were derived from two-way fixed-effects regressions using the IV of QR code campaigns. First, the estimated coefficient on QR code payments is around one when the dependent variable is outflows excluding saving and QR code payments during the week of the transaction. In other words, a 1,000 Japanese yen (JPY) increase in QR code payments prompted by campaigns leads to a 1,000 JPY increase in other spending. This outcome suggests the possibility that subdued salience associated with QR code payments stimulates spending. However, the effect of QR code payments is transitory. When the dependent variable is outflows in weeks after QR code payments, the coefficient on QR code payments is no longer significant. This implies that the impact of QR code payments on spending diminishes rapidly over time.

As Riksbank (2020) emphasizes, cash-free is not problem-free. Households are heterogeneous, and some find it hard to cope without cash. We confirm that QR code users tend to be younger, which aligns with expectations. Regardless of campaigns, younger people exhibit a higher propensity for QR code payments. Conversely, the effect of QR code campaigns on such payments is more pronounced among older individuals. Furthermore, this effect is amplified among individuals with greater wealth and less dependence on cash before the advent of QR code payments. In terms of the effects on outflows, we observe amplified impacts among individuals who previously relied more on cash.

Additionally, regarding age, the effects of QR code payments manifest in a U-shaped pattern: both younger and older individuals display an increase in outflows, while those in the middle (35–49 years old) exhibit an insignificant change.

While many empirical studies have been conducted on the effects of cashless payments, we cite three seminal papers: Jack and Suri (2014) on mobile money in Kenya, Bachas et al. (2021) on debit card provisions in Mexico, and Agarwal et al. (2022) on demonetization in India. Jack and Suri (2014) investigate the effects of a mobile money innovation (M-PESA) on consumption, and establish that M-PESA allows users to mitigate a negative shock by lowering transaction costs and improving risk sharing. Suri (2023) also conducts an excellent survey on mobile money, providing ample examples of decreasing transaction costs, particularly for those who barely had access to traditional banks. In India, the government unexpectedly removed existing banknotes in circulation from legal tender in 2016, which forced people to use cashless payments while new banknotes were not widely circulated. Agarwal et al. (2022) examine the effect of cashless payment adoption on spending using supermarket chain data and demonstrate that individuals increased their spending more as their prior cash dependence is higher. Furthermore, this increase is due to subdued salience rather than reduced transaction costs because an increase in spending with online retailers is small. Based on a case study in Mexico, where debit cards were provided to cash transfer recipients, Bachas et al. (2021) establish that recipients reduce spending due to reduced transaction and monitoring costs. As indicated above, seminal works are concentrated in developing countries.[2]

While the present study complements the above literature on the effects of cashless payments, it offers two key advantages. First, a case in Japan provides valuable insights into the specific channels through which cashless payments impact spending, thereby highlighting the role of salience. Cashless payments can influence spending through various channels by reducing salience as well as reducing transaction costs and mitigating liquidity constraints. However, the transition from cash to QR code payments in Japan is unlikely to substantially reduce transaction costs, unlike cases in emerging economies.

[2]Studies for developed countries include Wong, Lau, and Yip (2020) and Brown et al. (2023). The former examines the relationship between cashless payments and economic growth in OECD countries, and documents a positive correlation. Using payment diary and survey data, the latter investigates how payment choices influence discretionary overspending. For Japan, Sekine, Shoji, and Watanabe (2022) and Fujiki (2022, 2023) investigate changes, choices, or effects of cashless payments in Japan.

This is because, in Japan, more than 97% individuals already have bank accounts (Bank of Japan 2021), and using and holding cash is not costly because ATMs are widespread with no/small withdrawal fee, Japan is a safe country to hold cash, and the nominal interest rate, the opportunity cost of holding cash, is effectively zero. Moreover, the adoption of QR code payments does not alleviate liquidity constraints in Japan either. Trust in banks is not a significant issue compared to other regions like Mexico.[3] Therefore, the identification of a significant change in spending following QR code payments suggests the importance of the salience channel in influencing consumer behavior.

Second, PayPay campaigns serve as an ideal IV to estimate the causal effects of QR code payments on spending. Endogeneity in the adoption of cashless payments poses a challenge for the causal inference, even though the arrival of new technology (e.g., mobile money M-PESA) or governmental policy (demonetization in India) is exogenous. Furthermore, a third factor, such as macroeconomic shocks, may influence both cashless payments and spending. To address this challenge, Agarwal et al. (2022) assume that prior cash dependence captures the forced switch to cashless payments and provide evidence to verify the validity of the identifying assumption. We leverage PayPay campaign information as an IV, which is exogenous and has variations in both time and regions. Consequently, two-way fixed-effects regression models can be effectively applied. Bachas et al. (2021) investigate debit card provisions, which have a similar variation across time and regions.

Consumer salience, which is a concept explored across behavioral economics, policy studies, and marketing literature, is often referred to by different names; the pain of paying, which is a phenomenon Prelec and Simester (2001), Soman (2003), and Spantig (2021) investigate via field experiments. Broader examinations of consumer behavior include Thaler's (1999) review of mental accounting, which is the set of cognitive operations used by individuals to manage their financial activities. Brown et al. (2023) examine the relationship between cashless spending and overspending, with an emphasis on present-focused preferences. The concept of subdued salience is also associated with impulse buying/spending and has been studied extensively in marketing (e.g., Clover 1950, Muruganantham and Bhakat 2013, Iyer et al. 2019). Our study makes a novel contribution to this body of literature by presenting empirical evidence on the causal ef-

[3]Consumer loans can influence a liquidity constraint. While PayPay offers consumer loans via the PayPay Bank, a connection between QR code payments and consumer loans is weak and the consumer loan market in Japan is not as large as that in the U.S. except for mortgages.

fects of cashless spending through changes in salience, which are drawn from real-world events in Japan that promoted cashless spending initiatives.

The remainder of this paper is structured as follows. Section 2 explains the research background and describes the data. Section 3 outlines our estimation methods and results. Section 4 concludes.

2 Research Background and Data

2.1 Cashless Payments in Japan

Cashless payments are transactions conducted without the use of physical currency, such as coins or banknotes, and include direct debit and transfers using bank accounts, credit or debit card payments, and payments using mobile phones.[4] Compared with other countries, the ratio of cashless payments for Japan remains low (Ueda 2024). For example, a report by the Ministry of Economy, Trade and Industry for Japan (METI 2023) documents that the ratio of cashless payments is 32.5% as of 2020, compared to 93.6% in South Korea, 55.8% in the U.S., and 46.3% in Sweden.

However, cashless payments have been rapidly spreading globally, and Japan is no exception. One driving force is QR code payments, which are commonly used for various purposes, including retail purchases, bill payments, peer-to-peer transfers, and more. Launched in 2018, PayPay in Japan has played a significant role in driving the adoption of cashless payments. According to PayPay (July 7, 2023), its share in QR code payments is 67%.

QR code payments boomed in 2020 for the following two reasons. The first was mounting demand for contactless payments as a result of the COVID-19 pandemic, while cash was avoided. The second was various promotional campaigns by PayPay to incentivize users to adopt cashless payments. PayPay launched large-scale campaigns in collaboration with local governments from July 2020 to February 2021. In the campaigns, users can receive a rebate of around 20–30% if they make a payment using PayPay at designated merchants (e.g., supermarkets, restaurants, convenience stores) in the re-

[4]Direct debit (direct withdrawal) is a transaction in which an organization withdraws an undetermined amount of money automatically from users' accounts given the pre-authorization of payments at the bank account. Outflows using direct debit include regular automatic payments such as withdrawals of utility bills, rent, and school fees.

gion. The rebate is transferred to the user's PayPay account 30 days after the payment. Data on past campaigns are collected from the PayPay website.[5] They reveal that 105 municipalities, mostly at the city/town level except for two cases of the prefecture level, participated in PayPay campaigns from July 2020 to February 2021, and that 12 municipalities conducted PayPay campaigns twice or three times. The mean duration of campaigns was 6.75 weeks.

We focus on only PayPay as the method of QR code payments. This is because PayPay is the market leader in such payments and its campaigns provide an ideal exogenous variation across time and region to derive a causal inference for the effect of cashless payments on spending. Hereafter, we use QR code and PayPay interchangeably.

2.2 Bank Account Transaction Data

We use novel bank account transaction data thanks to the collaboration between Mizuho Bank and Waseda University. Mizuho Bank is one of the three largest banks in Japan, with approximately 24 million accounts held by individual customers (one out of every five people in Japan).[6] The data were made available through a strict contract between Mizuho Bank and Waseda University, and analyzed in a setting in which measures were taken to prevent the identification of individuals, such as masking and other anonymous processing.

The transaction data record all transactions involving Mizuho Bank, including automatic teller machine (ATM) cash withdrawals, payroll receipts, utility bill payments, and bank transfers. Outflows (inflows) are defined as all the transactions that decrease (increase) the amount of their deposits. All of the transactions are assigned identification codes and remarks in Japanese, from which we collect several specific transactions.

The record of PayPay payments is collected from the outflows that are accompanied by the remark "paypay corporation" before March 2021 or "paypay" after March 2021 (the remark changed in March 2021). This transaction indicates that an individual transfers money from the individual's bank account to PayPay account. The following two points should be noted. First, PayPay payments in this study do not mean payments using PayPay accounts at merchants. Rather, we measure a money transfer to PayPay accounts, and the timing of PayPay payments precedes that of spending using such

[5]https://paypay.ne.jp/event/support-local-end (in Japanese).
[6]https://www.mizuho-fg.co.jp/investors/individual/strength/index.html

accounts at merchants. Second, other methods of money transfers to PayPay accounts exist, which our data cannot track. They include transfers using cash or credit cards. PayPay users can use certain ATMs (often installed at convenience stores) to deposit cash to their accounts; however, Mizuho Bank's ATMs do not provide this service and we cannot know how cash is used. In addition, PayPay users can transfer money to their accounts once they register their credit cards. However, the Mizuho Bank data do not provide information on this specific transaction (i.e., how much they spent in transferring money to PayPay accounts using credit cards), although they provide the sum of monthly amount spent using credit cards. According to an internet survey of QR code users, the most frequent method of transfers is a credit card (36%), followed by cash (18%) and transfer from a bank account (17%).[7] This data limitation decreases the sample of PayPay payments in our study.

The Mizuho Bank data also record the balance of deposits and annualized income at the end of each month and information on personal characteristics such as the year of birth, gender, and registered address data at the municipality level. We define wealth as the balance of deposits at Mizuho Bank, which is the sum of demand deposits, time deposits, other banking accounts, public bonds, mutual funds, and life and non-life insurance balances. Annualized income is labor earnings based on either the actual amount of salary and bonus in the last year (after tax and social contribution) paid to users' accounts or the self-reported amount. The latter information is often collected when users open their bank accounts or apply for a mortgage.

It should be noted that information on transactions at other financial institutions, especially securities companies and postal savings accounts, is not available. Since many account users hold accounts with institutions other than Mizuho Bank, the deposits and withdrawals recorded in this data do not necessarily capture all of an individual's transactions. In particular, information on non-liquid financial assets, such as stocks, which are often invested in securities companies, is largely omitted.

2.3 Overview of the Data

The time frame is from January 2020 to June 2021, which is the period when QR code payments spread rapidly in Japan and four months since the large-scale first wave of

[7]The survey was conducted by MMDLabo Co. in June 2023 and 6,733 QR code users responded. See https://mmdlabo.jp/investigation/detail_2236.html (in Japanese).

PayPay campaigns ended in February 2021. The time unit is one week, 79 weeks in total.

The individuals analyzed are those who used PayPay at least once and lived in one of the PayPay campaign regions. More specific conditions are as follows. They transferred money from their Mizuho bank accounts to PayPay accounts at least once from January 2020 to February 2021. Their registered address of residence at the end of 2020 was in the municipality where PayPay campaigns were conducted from July 2020 to February 2021. They used their bank accounts at least 18 weeks out of 79, which is imposed for excluding virtually dormant accounts. Data are a balanced panel, in which no transaction is filled with value 0, although control variables such as log wealth and log annual income may take an NA (not available) in the following regressions.

The descriptive statistics of the transaction data at the individual level as of 2020 for approximately 100,000 individuals are presented in Table 1. To maintain anonymity, the maximum and minimum values are not given. The mean amount of inflows and outflows excluding saving is around 5.1 and 4.4 million JPY, respectively (1 US dollar $\sim$ 150 JPY). While the mean amount of cash withdrawals is 760 thousand JPY, that of QR code payments (through PayPay) is far smaller, around 150 thousand JPY. According to the mean frequency of transactions, these individuals use QR code payments in 13 weeks out of total 53 weeks, while they withdraw cash in 10 weeks. The mean log wealth and log annual income are 5.8 and 5.7, respectively, which suggests that mean wealth and annual income are 322 thousand and 304 thousand JPY. The mean age is 41 and 43% of the individuals are female.

Some further results on QR code payments are presented in Figure 1. The top left-hand panel shows the time-series change in the fraction of individuals who have used the QR code at least once since January 2020. By construction, this variable converges to one at the end of our observation period. The panel illustrates a gradual and steady increase in PayPay users; more specifically, two notable increases are observed in January 2020 and around August 2020. In fact, the latter period corresponds to the period of PayPay campaigns, which is indicated in the top right-hand panel as the time-series change in the fraction of individuals under such campaigns. We calculate this by searching the region of residence at the municipality level for each individual at the end of 2020 and taking the value of 1 for each individual and week if the individual lives in a municipality under PayPay campaigns in the week, and 0 otherwise. The panel reveals that PayPay campaigns were conducted from July 2020 to February 2021, and at its peak, around

60% of individuals were under the campaign. Further, this panel indicates a considerable variation in the campaigns across time and individuals. The bottom left-hand panel presents the time-series change in the amount spent on PayPay. While it exhibits a trend increase, the campaigns did not appear to contribute to a marked temporal increase in the amount spent on PayPay. Finally, the bottom right-hand panel shows the histogram of the amount spent on PayPay per transaction. A peak is observed at 10,000 JPY followed by 5,000 or 1,000 JPY, indicating that individuals tend to transfer a round amount of money to PayPay accounts.

Representativeness of our sample is an important issue. Our sample does not include individuals who live outside PayPay campaign regions or never use PayPay. We are confident that the regions are representative as they are scattered across Japan and include both small and large cities/towns. However, the adoption of PayPay is endogenous, and individuals who use PayPay are likely to be different from those who never do so.

Further Analysis by Expanding Data To check the representativeness for an intermediate size of individuals, we take bank users who live in a medium-sized city, Warabi city in Saitama prefecture (a neighboring prefecture to Tokyo), and compare basic characteristics between PayPay users and non-users. Specifically, the bank users are selected such that their residence at the end of 2020 is Warabi city and they make transactions using their Mizuho bank accounts at least 18 weeks out of 54 weeks in 2020.

Figure 2 graphically illustrates the representativeness of PayPay users in Warabi city. The top panel indicates the time-series change in the fraction of individuals who spend on PayPay each week, where the interval between the two red lines corresponds to PayPay campaign weeks. The panel suggests that the fraction of PayPay users steadily increases but remains small at around 0.04 at most. The bottom four panels show the comparison between PayPay users and non-users, where the former is defined as the individuals who spend on PayPay at least once in 2020. One clear finding is that PayPay users are younger. Regarding the amount of cash withdrawals, wealth, and income, non-users have bimodal distribution, with one peak at zero. Ignoring observations at zero, we can find that PayPay users and non-users are similar in terms of the amount of cash withdrawals, wealth, and income.

3 Estimation

In this section, we explain our estimation strategy and estimation results.

3.1 Estimation Strategy

To estimate the effect of QR code payments on spending, we run the following regression:

$$C_{it+h} = \gamma^h QR_{it} + \alpha_i + \alpha_t + \beta Z_{it} + \varepsilon_{it}, \tag{1}$$

where C_{it} represents the amount of spending for individual i in week t, QR_{it} is the amount of QR code payments, and Z_{it} are control variables consisting of total inflows in week t and log wealth and log annual income recorded in the previous month. The measure of spending for C_{it} is defined as total outflows excluding saving and QR code payments in week t (outflows). Saving is outflows that are accompanied by the remark of either "shoken (securities)" or "gohensai (repayment)," which is indicative of transfers to securities companies and loan (mortgage) repayments, respectively. As an alternative measure of C_{it}, we also use outflows associated with cash withdrawals from ATMs, which indicates cash demand. For wealth and annual income, we add 1 to each variable and take a logarithm because it may take 0. Two-way fixed effects α_i and α_t control time-invariant heterogeneity across individuals and the effects of aggregate time-series developments, such as the state of emergency declaration under the COVID-19 pandemic and an increase in contactless payments, on aggregate spending. The standard errors are clustered at the individual level. Individuals in a control group are not those who never use QR code payments, but those who have experience of using such payments at least once before the end of June 2021. In the sample, the amount and timing of these payments differ among individuals.

Here, coefficient γ^h is the coefficient of interest. We run the regression for not just contemporaneous timing $h = 0$ but also various $h's$, motivated by the local projection method developed by Jordà (2005). Thus, γ^h indicates the extent to which spending has changed the $|h|$ week before ($h < 0$) or after ($h \geq 0$) a QR code payment. Note that C_{it} excludes QR_{it}, and thus, $\gamma^h > 0$ suggests that a QR code payment stimulates spending. Conversely, if $\gamma^h < 0$, QR code users decrease their spending: particularly, when $\gamma^h = -1$, an increase in QR code payments leads to a decrease in other spending by the same amount.

We use PayPay campaign information as an IV. QR code payments are endogenous and possibly cause a bias in estimate γ^h for the following two reasons. First, individuals may change their preferences between cash and cashless methods of payments, and a substitutability between cash and cashless yields a negative coefficient γ^h. Second, a third factor, especially aggregate demand shocks, likely influences both C_{it} and QR_{it} in the same direction, yielding a positive coefficient. To estimate the causal effects of QR code payments on spending, we use PayPay campaign information, $Camp_{it}$, as an IV, which takes the value of 1 if individual i lives in the region under a PayPay campaign in week t and 0 otherwise. Specifically, the first-stage regression is as follows:

$$QR_{it} = \delta^C Camp_{it} + \delta^X Camp_{it} \cdot X_{it} + \alpha_i + \alpha_t + \beta Z_{it} + \nu_{it}. \tag{2}$$

This PayPay campaign variable varies over time and region, and is exogenous and random to individuals. PayPay campaigns may well increase demand in the region, but this works only through increased demand for QR code payments. That is, a rebate from the campaigns increases household income, which may increase regional demand. However, without QR code payments, individuals cannot earn a rebate, which warrants the use of PayPay campaign information as an IV. In addition to $Camp_{it}$, we use its interaction terms with individual i's characteristics in week t, X_{it}, as IVs to account for a variation in QR code payments across individuals. Specifically, X_{it} is a vector consisting of age, gender, and log wealth.

Regarding our causal inference, two kinds of concerns may exist. The first is that campaigns directly affect spending by providing a rebate. However, note that a rebate provided by a campaign is not counted in our measure of spending because it does not involve bank account transactions.[8] It also should be noted that the rebate likely influences γ^h after $h \geq 4$ rather than $h < 3$ because it is provided 30 days (4 weeks) after the payment. It is probable that the anticipation of the rebate leads to increased spending from $h = 0$ through the income effect. If this is the case, γ^h would exhibit a step function-like increase as individuals begin to anticipate the rebate. However, the effect of the rebate on permanent income is expected to be relatively small. The second concern is an endogeneity in adopting QR code payments in response to campaigns. Some individuals may be sensitive to campaigns, while others may not. This heterogeneity may

[8] Indirectly, a rebate may both increase and decrease our measure of spending. On the one hand, spending may increase, because a rebate increases income. On the other hand, spending may decrease if individuals use the rebate to make a payment and total payments are unchanged.

generate a bias in estimate γ^h if this heterogeneity is correlated with the effect of QR code payments on spending (e.g., individuals who are sensitive to campaigns are more likely to increase spending after the adoption of QR code payments.) However, we find no clear reason to believe that this correlation exists. Furthermore, heterogeneity is controlled in our regression to some extent by including two-way fixed effects, wealth, and income.

Whereas the benchmark regression reveals the elasticity of intensive margin, for example, how much a one-yen increase in QR code payments changes spending, another question arises regarding an extensive margin, that is, how much the experience of using such payments changes spending. To explore this effect, we change the explanatory variable and run the following regression:

$$C_{it+h} = \gamma^h I_{it}^{QR} + \alpha_i + \alpha_t + \beta Z_{it} + \varepsilon_{it}, \tag{3}$$

where I_{it}^{QR} represents the experience of QR code payments for individual i in week t; it takes 1 if the individual used QR code payments at least once before or in week t and 0 otherwise. Coefficient γ^h suggests how much the experience of using QR code payments increases spending.

3.2 Effects of PayPay Campaigns (First-Stage Regression)

Before examining the effects of QR code payments on spending, we investigate those of PayPay campaigns on these payments and other variables. While this investigation corresponds to the first-stage regression, it will be meaningful by itself in considering the effectiveness of cashless promotion policy.

Tables 2 and 3 show the estimation results on equation (2) and alike. In column (1), the coefficient on PayPay campaign dummy $Camp_{it}$ is significantly positive, suggesting that PayPay campaigns increased QR code payments by 1,200 JPY. Columns (2) and (3) are the estimation results when we include interaction terms of $Camp_{it}$ and X_{it}. Because X_{it} has non-zero mean, the coefficient on PayPay campaign dummy $Camp_{it}$ is no longer meaningful. Column (2) corresponds to our benchmark first-stage regression, and the coefficients on the interaction terms with $Camp_{it}$ suggest that the effect of PayPay campaigns increases with ages, female dummy, and wealth. In column (3), we include prior cash dependence in X_{it}, which is defined as the fraction of the amount of cash withdrawals to 1 plus the amount of outflows excluding saving in the first eight weeks from January 2020 at the individual level. This cash ratio is intended to capture how much individuals relied on cash when they made transactions before PayPay campaigns started. If QR code payments are a substitute to cash payments, we expect the coefficient on the interaction term to be positive. However, the estimated coefficient is negative. That is, individuals tend to increase their QR code payments in response to the PayPay campaigns more as they rely on cash less, which implies that cash and QR code payments are not necessarily a substitute.

Table 3 presents further estimation results. In columns (4) and (5), we take a logarithm for the dependent variable. Specifically, column (4) suggests that PayPay campaigns increased QR code payments by 0.66 in log (i.e., by 93%). Columns (6) to (8) indicate the estimation results when we change the dependent variable to the experience of QR code payments given by I_{it}^{QR}, amount of cash withdrawals, and amount of outflows, respectively. Although some coefficients on interaction terms are significantly different from zero, PayPay campaigns do not appear to have a material influence on these variables, because coefficients on $Camp_{it}$ are insignificant.

Further Analysis by Expanding Data Since we believe that investigating the effectiveness of cashless promotion policy is valuable, we conduct a further analysis by expanding data. It should be noted that our main data consist of individuals who have experienced QR code payments only. A considerable number of individuals have no QR code payments experience, as presented in Section 2.3 via the analysis of residents in Warabi.

We expand the region to nationwide Japan and individuals to all bank account users. However, since the size of the data prevents computations, we impose the following conditions to reduce a data size. A time frame is a month, which consists of the following four months: January 2020, February 2021, June 2021, and one year after the end of our data June 2022. Individuals use their Mizuho Bank accounts to make transactions of 10,000 JPY outflows or more in all of the above four months. Then, we collect data on approximately six million individuals (i.e., 60 times), comprised of their area of residence, the amount of outflows, the amount of QR code payments, and so on. Using information on the area of residence as of December 31, 2020, we identify whether they lived in the region where PayPay campaigns were conducted from July 2020 to February 2021.

How the fraction of QR code users changed from January 2020 to June 2022 is detailed in Table 4. In January 2020 before the PayPay campaigns, almost no difference exists in the fraction of QR code users between those in the PayPay campaign region and those outside, that is, approximately, 0.036 (i.e., 3.6%). However, in February 2021, when the PayPay campaigns ended, the fraction increased to 0.065 in the PayPay campaign region, compared with 0.057 outside the region. Moreover, this campaign effect is long-lasting: in June 2022, approximately 18 months after the PayPay campaigns, the difference in the fraction of QR code users between the two regions remains: the fraction of users in the campaign region is 0.108, while that outside the region is 0.099. The difference is 0.009, which indicates that PayPay campaigns increase QR code users by 0.9% of the total population under the campaigns. This table also presents the amount of QR code payments per capita, which is the mean or median of the amount of QR code payments in the four months. This reveals that the amount of QR code payments per capita is greater in the PayPay campaign region than outside.

We scrutinize this result by running the following difference-in-differences regression:

$$\Delta Y_i = aCamp_i + bZ_i + \varepsilon_i, \tag{4}$$

where ΔY_i represents a change in a certain variable from January 2020 (before the campaign) for individual i and $Camp_i$ is a PayPay campaign dummy, which takes the value of 1 if individual i lived in the region under the PayPay campaign. For Y_i, we use a QR use dummy to indicate whether individual i uses QR code payments in a certain month or the amount of QR code payments, and three timings: February 2021, June 2021, and June 2022. Finally, Z_i captures individual characteristics. Standard errors are clustered at the prefecture level, not at the individual level, because of the gigantic size of the data.

Table 5 shows the estimation results. The coefficient on a PayPay campaign dummy in column (1) is 0.009, which suggests that the campaign increases the fraction of QR code users by 0.9% points at the end of the campaign period. Further, this effect is persistent in that the coefficients in columns (2) and (3) are almost unchanged at 0.010 and 0.009 in June 2021 and June 2022, respectively. The size of this effect is also consistent with the results in Table 4. Columns (4) to (6) reveal that the PayPay campaign increases the amount of QR code payments at the individual level by around 400 JPY. Further, columns (1) to (6) indicate that coefficients on age tend to be negative, while those on log wealth are positive. This suggests that, irrespective of PayPay campaigns, younger and more wealthy people tend to use QR code payments more.

Finally, it should be noted that the size of the campaign effect, that is, 0.9% on the fraction of QR code users is likely conservative, the lower bound. This is because, as explained in Section 2.2, the Mizuho Bank data allow us to analyze only one of many transfer methods to PayPay accounts, and we are unable to analyze transfers using cash or credit cards. Considering that the share of a bank account transfer in the most frequent method of transfers is 17%, the size of the campaign effect may be as large as 0.9% $\times$ 1/0.17= 5%. Furthermore, the campaign effect may be amplified, because QR code users from neighboring regions can participate in shopping within the region under the campaign, which is not accounted for in our estimation. However, it is essential to acknowledge that this campaign effect encapsulates not only consumers' responses but also the reactions of merchants and local governments. It is highly plausible that, during the campaign period, merchants and local governments implemented strategies to encourage QR code payments, such as adopting the necessary technology to accept the QR code payment or offering subsidies.

3.3 Effects of QR Code Payments (Second Stage Regression)

Table 6 shows one of our main estimation results, which corresponds to the regression of equation (1) for the contemporaneous week of $h = 0$. Column (2) indicates that the coefficient on QR_{it}, γ^0, is positive at 1.07. Although it is significant only at the 10% level, the coefficient is robustly positive and often significant at the 5% level under various specifications. This result suggests that QR code payments stimulate outflows excluding QR code payments by the same size in the week of transaction.

This result suggests that subdued salience stimulates spending. In the case of PayPay in Japan, transaction or monitoring costs and liquidity constraints are unlikely to change due to cashless payments. Using and holding cash is not costly because ATMs are widespread with no/small withdrawal fee, Japan is a safe country to hold cash, and the nominal interest rate is effectively zero. The adoption of QR code payments does not alleviate liquidity constraints in Japan either.

Column (4) reveals that, when the dependent variable is a narrower outflow component, the amount of cash withdrawals, coefficient γ^0 is insignificant. Column (6) is the estimation result for equation (3). Although a wide confidence interval and significant only at the 10% level, this suggests that experiencing QR code payments increase outflows by 45,000 JPY.

For comparison, we present the estimation results without IV (i.e., ordinary least squares (OLS)) in columns (1), (3), and (5). Column (1) indicates that, when we do not use IV, γ^0 is not significantly different from zero. A comparison with the positive coefficient for IV suggests that a shift of preference for the methods of transaction from cash to the QR code causes a downward bias in the estimate of γ^0 when we use the OLS.

Dynamic effects of QR code payments are presented in Table 7 and Figure 3, where we estimate equation (1) for each h from -4 to 6. When the dependent variable is outflows, coefficient γ^h is insignificant for all $h's$ except $h = 0$. Thus, the effects of QR code payments on spending are transitory, even though they may be significant in the very short run.

Heterogeneity We examine heterogeneity in the effects of QR code payments on outflows. Accordingly, we divide individuals into groups by their characteristics based on prior cash dependence, age, gender, and wealth, where prior cash dependence is the same as that used in Section 3.2.

Figure 4 illustrates the estimation results. Regarding prior cash dependence, the effects of QR code payments on outflows are the largest and significant for the third quantile group of individuals, who relied on cash relatively more before the advent of QR code payments. Regarding age, the effects of QR code payments are U-shaped: young (20–34 years old) and old (50–65 years old) tend to significantly increase outflows, whereas individuals in the middle (35–49 years old) do not make significant changes in their spending. Regarding wealth, the effects of QR code payments on outflows are increasing with wealth, although the coefficients are insignificant in all the groups. Finally, for gender, only men increase their outflows significantly.

Robustness Checks We conducted robustness checks on our estimation results, as presented in Table 8. Particularly, columns (2) to (5) strengthen our main findings, demonstrating a significantly positive coefficient on QR code payments. First, we employ different fixed effects: only individual fixed effects in column (2) and individual and week×prefecture fixed effects in column (3). The latter intends to control aggregate changes at the prefecture (a larger region) level, although we are then unable to analyze two campaign events that were held at the prefecture level. The estimated coefficients on QR code payments are significant, hovering around 2 in both cases. Second, we use different IVs. In column (4), the IV is only the PayPay campaign dummy, whereas it consists of the dummy and the interaction term with log wealth in column (5). The estimated coefficients on QR code payments are both significantly positive at around 1. Finally, we use the logarithm of outflows as the dependent variable, which reveals that the coefficient turns to negative (column (4)).[9]

4 Concluding Remarks

In this study, we leveraged bank transaction data and the occurrence of QR code campaigns in Japan to investigate the impact of cashless payments on consumer spending behavior. Our estimation results suggest the possibility that subdued salience due to cashless payments stimulates spending. However, while this effect is significant in the immediate week of transactions, it becomes statistically insignificant thereafter. Thus, cashless spending is unlikely to stimulate spending persistently. Nevertheless, our estimation results also demonstrate that the effect of QR code campaigns endures over time, as evidenced by a sustained increase in the number of QR code users.

Future research may expand upon this study by examining a broader spectrum of cashless payment methods. While the current study focuses on a particular type of cashless payments, QR code payments promoted by campaigns, various other cashless payment methods exist, including credit cards and CBDC. Each payment method inherently possesses distinct characteristics warranting further investigation.

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Table 1: Descriptive Statistics of the Transaction Data as of 2020

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Inflows	101,310	5,120,397	15,884,031	1,320,000	3,175,652	5,564,193
Outflows exc saving	101,310	4,360,163	12,553,332	1,173,625	2,821,252	5,016,437
Outflows exc saving and QR code payments	101,310	4,210,732	12,536,583	1,047,800	2,662,574	4,844,736
QR code payments	101,310	149,431	230,906	20,000	69,500	190,967
Cash withdrawals	101,310	760,187	1,346,403	30,000	300,000	970,000
Freq of outflows	101,310	36.561	12.464	28	39	47
Freq of QR code payments	101,310	12.803	12.572	3	8	20
Freq of cash withdrawals	101,310	9.965	10.878	1	6	16
Salary	101,310	1,590,294	2,195,039	0	650,000	2,750,634
Log wealth	97,269	5.779	2.195	4.364	5.917	7.372
Log income	97,269	5.720	3.620	0.000	7.807	8.395
Female dummy	96,349	0.430	0.495	0.000	0.000	1.000
Age	97,267	41.087	12.743	30.906	39.906	50.906

Note: The table summarizes actual transactions in 2020 for the individuals in our data. The monetary unit is Japanese yen. Wealth and income are expressed as the mean of the log of one plus total deposits and annual income, respectively, in thousand yen. Freq (frequency) indicates how many weeks individuals make transactions in 53 weeks. To maintain anonymity, we do not report the maximum or minimum values.

Table 2: Effects of PayPay Campaigns (First Stage)

	(1)	(2)	(3)
		Dependent variable	
		QR code payments	
Campaign dummy	1242.5802***	-611.7993***	-541.4758***
	(20.163)	(84.835)	(87.810)
Inflows	7.68e-05***	7.87e-05***	7.87e-05***
	(0.000)	(0.000)	(0.000)
Log wealth	440.9246***	430.8865***	430.2187***
	(8.725)	(8.829)	(8.822)
Log income	46.8481***	50.0605***	51.3107***
	(6.424)	(6.238)	(6.269)
Campaign dummy*age		21.7574***	21.5126***
		(1.304)	(1.301)
Campaign dummy*female dummy		262.7427***	250.9082***
		(34.687)	(34.792)
Campaign dummy*log wealth		100.5343***	104.7985***
		(7.605)	(7.911)
Campaign dummy*log income			-11.955**
			(5.175)
Campaign dummy*cash ratio			-0.0039**
			(0.002)
Fixed effects		individual, week	
No. of observations	7,781,668	7,709,915	7,709,915
No. of individuals	98,784	97,887	97,887
No. of weeks	79	79	79
R^2	0.159	0.159	0.159

Note: Figures in parentheses indicate standard errors clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Logarithm is taken after adding 1.

Table 3: Effects of PayPay Campaigns (First Stage, 2)

	(4)	(5)	(6)	(7)	(8)
	Dependent variable				
	Log QR code payments	Log QR code payments	Dummy of QR experience	Cash withdrawals	Outflows exc saving and PayPay
Campaign dummy	0.6561***	-0.040	0.004	-321.181	2557.048
	(0.008)	(0.032)	(0.004)	(394.956)	(2600.899)
(Log) inflows	0.0381***	0.038***	8e-04***	0.0024***	0.4676***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.074)
Log wealth	0.2384***	0.2353***	0.0131***	2602.4035***	19712.7376***
	(0.003)	(0.003)	(0.000)	(52.794)	(774.873)
Log income	0.0454***	0.0461***	0.0073***	126.7802***	-457.1852***
	(0.003)	(0.003)	(0.000)	(29.409)	(166.319)
Campaign dummy*age		0.0062***	0.000	-4.833	-33.813
		(0.001)	(0.000)	(6.726)	(31.094)
Campaign dummy*female dummy		0.1763***	0.0137***	-371.3273**	-1221.539
		(0.013)	(0.002)	(164.199)	(842.363)
Campaign dummy*log wealth		0.0326***	0.000	186.1342***	357.803
		(0.003)	(0.000)	(42.883)	(304.668)
Fixed effects	individual, week				
No. of observations	7,781,668	7,709,915	7,709,915	7,709,915	7,709,915
No. of individuals	98,784	97,887	97,887	97,887	97,887
No. of weeks	79	79	79	79	79
R^2	0.305	0.306	0.593	0.112	0.456

Note: Figures in parentheses indicate standard errors clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Changes in QR Code Users after PayPay Campaigns

	No. of individuals	Fraction of QR users				
Campaign region		Jan 2020	Feb 2021	Jun 2021	Jun 2022	At least once
No	5,444,098	0.0358	0.0571	0.0664	0.0758	0.0985
Yes	717,195	0.0352	0.0652	0.0758	0.0841	0.1082

	QR code payments			
	Mean	Median	Mean	Median
Campaign region			among positive	
No	1,930	0	19,590	10,589
Yes	2,207	0	20,407	11,659

Note: We divide individuals into two groups by whether their registered address as of December 31, 2020 is in the area of PayPay campaigns. The fraction of PayPay users at least once indicates that of individuals who spent on PayPay at least once in the four months of Jan 2020, Feb 2021, Jun 2021, and Jun 2022. Mean and median among positive represent the mean and median of the amount spent on PayPay conditional on being positive.

Table 5: Effects of PayPay Campaigns: Diff-in-Diff Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Dummy of QR use			QR code payments		
	Feb. 2021	Jun. 2021	Jun. 2022	Feb. 2021	Jun. 2021	Jun. 2022
	Difference from the variable as of Jan. 2020					
Intercept	0.0561***	0.0752***	0.1022***	1448.4622***	2661.3388***	4287.3733***
	(0.002)	(0.002)	(0.003)	(89.664)	(211.529)	(330.169)
Campaign dummy	0.009***	0.0102***	0.009***	372.2987**	407.4751***	413.3513***
	(0.002)	(0.001)	(0.002)	(149.720)	(69.248)	(108.307)
Age	-9e-04***	-0.0013***	-0.0018***	-25.8791***	-50.7808***	-80.8197***
	(0.000)	(0.000)	(0.000)	(1.260)	(3.941)	(6.522)
Female dummy	0.007***	0.0099***	0.0145***	145.4636***	229.1542***	337.1418***
	(0.000)	(0.000)	(0.000)	(13.796)	(32.356)	(30.172)
Log wealth	0.000	4e-04***	6e-04***	40.0626***	126.9878***	152.1587***
	(0.000)	(0.000)	(0.000)	(2.905)	(18.340)	(27.877)
Log income	5e-04***	0.001***	0.0013***	18.3446***	61.0659***	89.5385***
	(0.000)	(0.000)	(0.000)	(1.728)	(9.399)	(11.735)
No. of observations	5,894,008	5,894,008	5,894,008	5,894,008	5,894,008	5,894,008
R^2	0.0066	0.0110	0.0177	0.0016	0.0032	0.0057

Note: Figures in parentheses indicate standard errors clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Effects of QR Code Payments

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Outflows exc saving and PayPay		Cash withdrawals		Outflows exc saving and PayPay	
	OLS	IV	OLS	IV	OLS	IV
Explanatory variables						
QR code payments	-0.064	1.0707*	0.0484***	0.100		
	(0.046)	(0.608)	(0.006)	(0.098)		
QR experience					-1153.287	45082.709*
					(1199.840)	(25353.364)
Inflows	0.4965***	0.4676***	0.0022***	0.0024***	0.4965***	0.4676***
	(0.074)	(0.074)	(0.000)	(0.000)	(0.074)	(0.074)
Log wealth	19774.997***	19278.6013***	2607.8534***	2577.8875***	19761.6465***	19166.2575***
	(736.117)	(835.436)	(52.325)	(68.249)	(733.060)	(827.989)
Log income	-478.4379***	-509.3278***	124.3456***	120.8633***	-472.9827***	-789.5204***
	(161.350)	(165.307)	(29.346)	(29.612)	(163.459)	(231.177)
Fixed effects	individual, week					
No. of observations	7,781,668	7,709,915	7,781,668	7,709,915	7,781,668	7,709,915
No. of individuals	98,784	97,887	98,784	97,887	98,784	97,887
No. of weeks	79	79	79	79	79	79
R^2	0.482	0.456	0.111	0.112	0.482	0.456

Note: Figures in parentheses indicate standard errors clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Dynamic Effects of QR Code Payments

Dependent variable	Outflows exc saving and PayPay				
Lead/lag h	-4	-3	-2	-1	0
Explanatory variables					
QR code payments	-0.007	-0.395	0.044	-0.486	1.0707*
	(0.842)	(0.846)	(0.867)	(0.784)	(0.608)
Inflows	0.005	-0.005	-0.005	0.000	0.4676***
	(0.007)	(0.005)	(0.005)	(0.005)	(0.074)
Log wealth	8316.919***	12473.6494***	15668.9271***	18260.862***	19278.6013***
	(1042.320)	(1099.511)	(1259.752)	(1264.735)	(835.436)
Log income	789.4497***	513.6128**	213.195	39.174	-509.3278***
	(254.305)	(252.530)	(243.554)	(239.605)	(165.307)
Fixed effects	individual, week				
No. of observations	7,324,499	7,420,853	7,517,207	7,613,561	7,709,915
No. of individuals	97,887	97,887	97,887	97,887	97,887
No. of weeks	75	76	77	78	79
R^2	0.050	0.050	0.049	0.049	0.456

Dependent variable	Outflows exc saving and PayPay					
Lead/lag h	1	2	3	4	5	6
Explanatory variables						
QR code payments	-1.137	-0.065	-0.591	-0.825	-0.825	-0.826
	(0.739)	(0.784)	(0.789)	(0.754)	(0.752)	(0.753)
Inflows	0.0321***	0.0273*	0.021	0.0234**	-0.001	0.000
	(0.011)	(0.015)	(0.016)	(0.012)	(0.005)	(0.006)
Log wealth	15908.2931***	13505.4652***	12370.8993***	11087.7983***	9669.5676***	8916.228***
	(1140.412)	(1120.933)	(1141.213)	(1091.304)	(1078.431)	(1086.191)
Log income	244.688	235.131	387.4909*	324.502	383.103	244.477
	(227.884)	(233.743)	(232.522)	(233.445)	(244.185)	(230.337)
Fixed effects	individual, week					
No. of observations	7,612,160	7,514,405	7,416,650	7,318,895	7,221,140	7,123,356
No. of individuals	97,887	97,887	97,887	97,887	97,887	97,887
No. of weeks	78	77	76	75	74	73
R^2	0.051	0.051	0.050	0.050	0.049	0.048

Note: Figures in parentheses indicate standard errors clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Effects of QR Code Payments (Robustness)

	(1)	(2)	(3)	(4)	(5)	(6)
	Benchmark	FE	FE	IV	IV	Log
Dependent variable		Outflows exc saving and PayPay (outflows)				Log outflows
Explanatory variables						
QR code payments	1.0707*	2.4316***	2.008**	1.2863**	1.3908**	-0.0142**
	(0.608)	(0.380)	(0.780)	(0.565)	(0.637)	(0.007)
Inflows	0.4676***	0.467***	0.4675***	0.4964***	0.4964***	1.29e-07***
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.000)
Log wealth	19278.6013***	18457.6063***	18865.936***	19178.8728***	19132.7707***	0.4278***
	(835.436)	(845.126)	(854.953)	(793.123)	(816.073)	(0.003)
Log income	-509.3278***	-678.2386***	-553.3463***	-541.4586***	-546.3323***	0.0626***
	(165.307)	(167.990)	(170.096)	(160.416)	(161.488)	(0.002)
Fixed effects	ind, week	individual	ind, week*prefecture	ind, week	ind, week	ind, week
IV		PayPay campaign dummy (A), A*age, A*female, A*log wealth		A	A, A*log wealth	A A*age, A*female, A*log wealth
No. of observations	7,709,915	7,709,915	7,709,915	7,781,668	7,781,668	7,709,915
R^2	0.456	0.454	0.455	0.482	0.482	0.391

Note: Figures in parentheses indicate standard errors clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

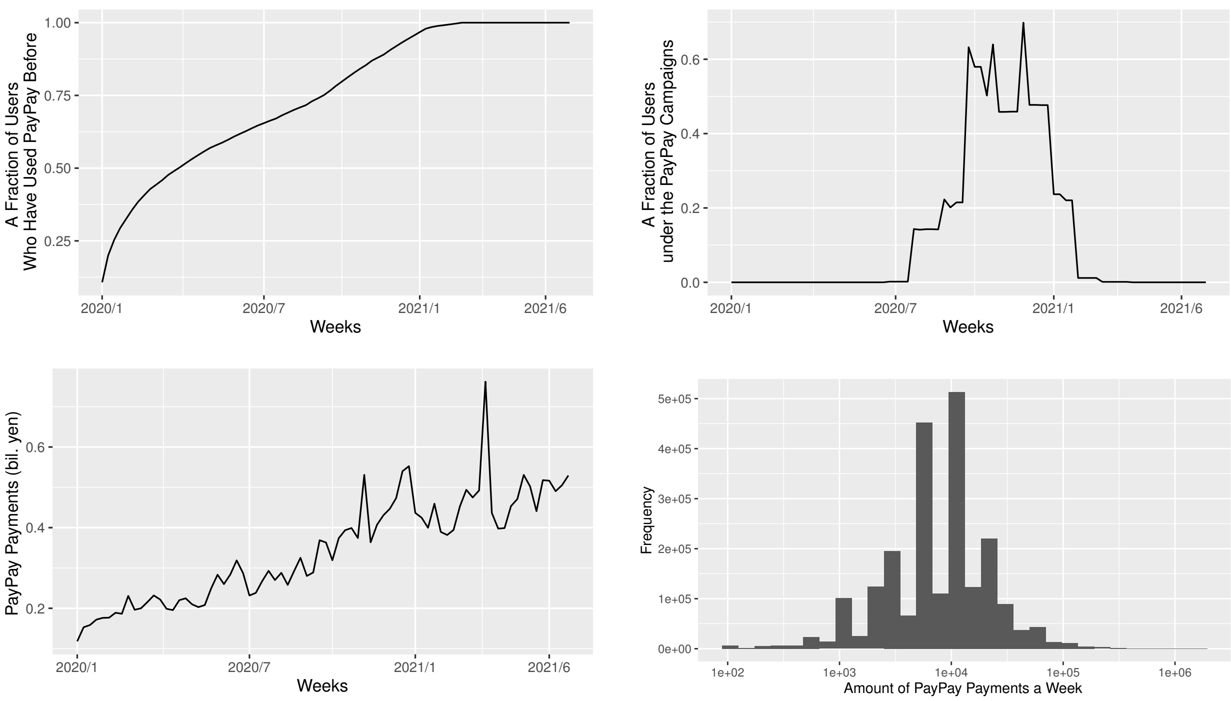

Figure 1: QR Code Payments

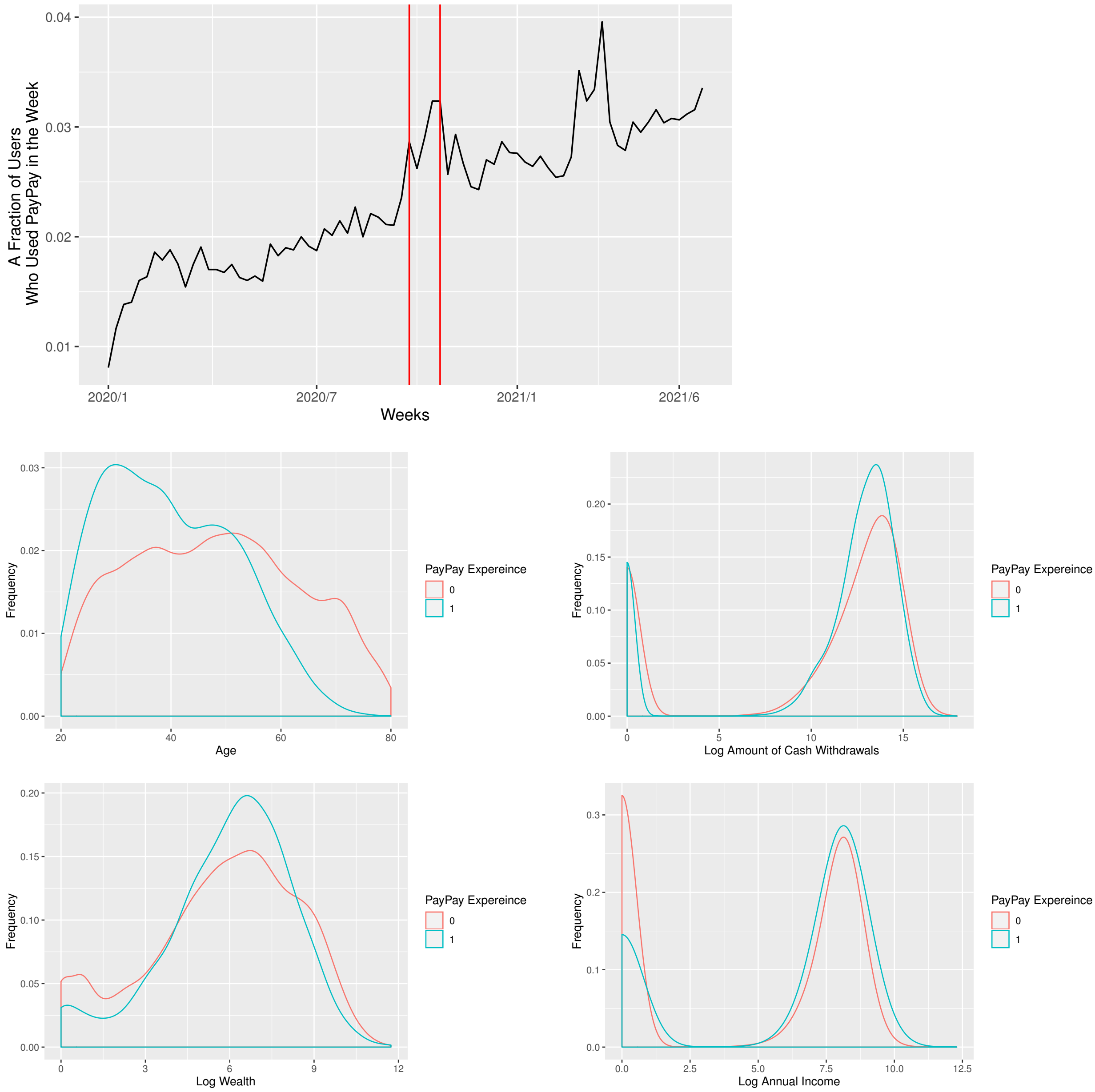

Figure 2: Comparisons of QR Code Payments Users and Non-Users

Notes: Individuals are residents in Warabi city in Saitama prefecture. In the top panel, the interval between the two red lines corresponds to the PayPay campaign weeks. In the bottom panels, individuals are assigned a dummy of 1 if they spend on PayPay at least once in 2020 and 0 otherwise. Amount of cash withdrawals, wealth, and income are taken a logarithm after adding 1.

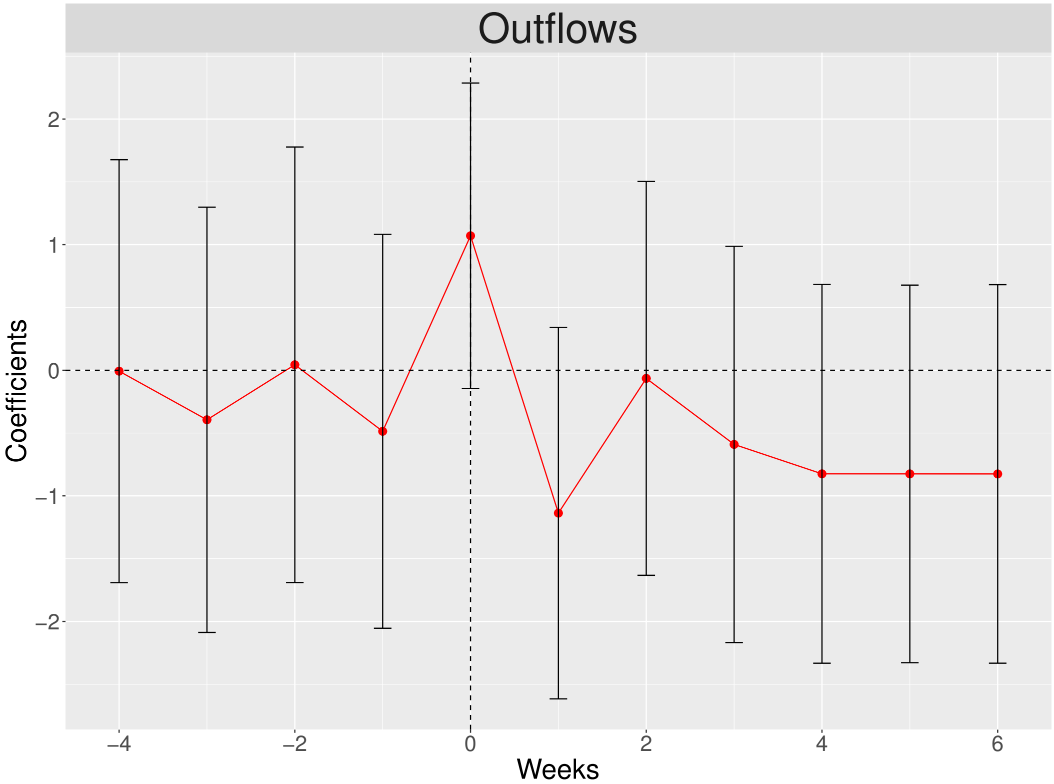

Figure 3: Effects of QR Code Payments on Spending

Notes: The coefficients on QR code payments are shown. Bars indicate 95% confidence intervals.

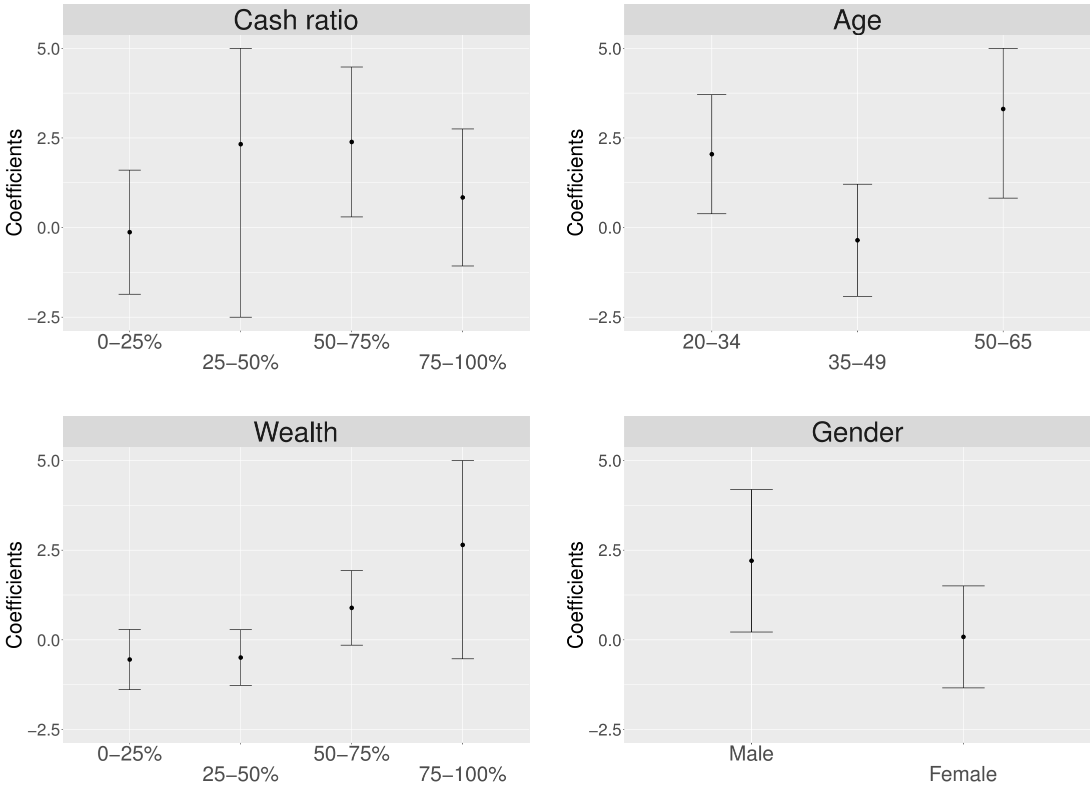

Figure 4: Effects of QR Code Payments on Spending by Groups

Notes: The coefficients on QR code payments are shown. Bars indicate 95% confidence intervals. Cash ratio is defined as the fraction of the amount of cash withdrawals to 1 plus the amount of outflows excluding saving in the first eight weeks from January 2020 at the individual level.