Going Cashless: Evidence from Japan's Point Reward Program

Toshitaka Sekine
Toshiaki Shoji
Tsutomu Watanabe

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Abstract

In October 2019, the Japanese government started a unique program that offered points (discounts) for cashless payments. Using credit card transaction data, we compare credit card usage at restaurants that participated in this program and those that did not. Our main findings are as follows. First, the number of card users was 9-12 percent higher in participating than in non-participating restaurants. Second, the positive impact of the program on the number of card users persisted even after the program ended in June 2020, indicating that the program had a lasting effect to promote cashless payments. Third, the impact of the program was significantly larger at restaurants that started accepting credit cards more recently, since the share of cash users at those restaurants was larger just before the program started. Finally, two-thirds of the difference between participating and non-participating restaurants disappeared during the first surge of COVID-19 in April 2020, suggesting that customers switched from cash to cashless payments to reduce the risk of infection both at participating and non-participating restaurants, but the extent to which customers switched was larger at non-participating restaurants with a larger share of cash users just before the pandemic.

JEL codes: E42, O33, O38

1 Introduction

The share of payments using cashless methods is much lower in Japan than many other countries. BIS statistics, for example, show that total payments via cashless means such as credit cards, debit cards, and e-money in Japan amounted to 74 trillion yen or 24 percent of household final consumption expenditure in 2018. This percentage is considerably lower than the 40 percent or more in other developed countries such as the United States, the United Kingdom, and Singapore. The social cost of relying on cash payments is substantial. For instance, using data for several European countries, Schmiedel et al. (2012) show that the unit cost of cash payments is higher than that of debit card payments. In addition, Rogoff (2015) argues that cash makes transactions anonymous, which potentially facilitates underground or illegal activities and leads to law-enforcement costs.

To raise the share of cashless payments, the Japanese government in October 2019 introduced a unique program offering reward points for cashless payments. The program, which ran until June 2020, provided an incentive to switch from cash to cashless payments by offering a discount of 5 percent. Government figures suggest that the program succeeded in raising the share of payments via cashless means.[1] The increase can be divided into two parts: the extensive margin and the intensive margin. Specifically, the extensive margin refers to the increase in the number of consumers newly using cashless payment means, while the intensive margin refers to the increase in the frequency or amount of cashless payments by those already using such means.

Using a dataset covering credit card transactions at restaurants in Tokyo, we examine the increase in cashless payments (especially the intensive margin) by comparing credit card usage at restaurants that participated in the point reward program and those that did not. Our main findings are as follows. First, we find that the amount paid via credit card was

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[1]According to the Ministry of Economy, Trade, and Industry of Japan, the share of cashless payments increased to 29.7 percent of household final consumption expenditure in 2020.

26-46 percent higher and the number of card users 9-12 percent higher at restaurants that participated in the program than in those that did not. This result suggests that the amount of credit card payments increased in response to the government's point reward program. This finding is consistent with the findings of studies such as those by Ching and Hayashi (2010) and Carbó-Valverde and Liñares-Zegarra (2011) showing that rewards offered by card issuers have a significant impact on consumers' choice of payment method.

Second, the positive impact of the program on the amount of credit card payments persisted even after the program ended in June 2020. This finding suggests that the program had a lasting rather than just a transitory effect in promoting cashless payments. In other words, once consumers switch from cash to credit card payments, they do not switch back. This is inconsistent with the framework proposed by earlier studies such as Alvarez and Lippi (2017), where consumers have multiple payment methods and choose the most convenient one at each payment opportunity. Rather, this finding suggests that the spread of credit card usage can be described as akin to the adoption process of new technologies or products, which economists have tried to model. One of the earliest examples is the model proposed by Griliches (1957), in which the fraction of adopters increases monotonically.

We present a simple framework of technology adoption, which illustrates how cash users in a restaurant switch to credit card payments. In this framework, the promotion of cashless payments leads some cash users to switch to paying by credit card. This means that the extent to which such promotion succeeds in getting consumers to switch depends on the percentage of cash users among total customers: the larger the percentage of cash users at a particular restaurant, the larger the impact of campaigns such as the point reward program is likely to be. We test this implication of our framework in two ways. First, we use the time elapsed since each restaurant started to accept credit card payments as a proxy for the share of cash users, given that this share is decreasing over time. This means that the point reward program had a smaller impact on restaurants that have been accepting credit card

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payments for longer. Second, we use the variation in the percentage of cash users across restaurants participating and not participating in the program. Before the program ended in June 2020, Japan was hit by the first surge of COVID-19 in April and May 2020, which provided an incentive for consumers to use cashless payment means in order to reduce the risk of infection. Given that the share of cash users was smaller in participating than in non-participating restaurants, we would expect the difference between the two in terms of customers' use of credit cards to decrease during this period. In this study, we provide evidence consistent with these arguments.

This study contributes to three strands of literature. The first is studies examining consumers' choice of payment method, both from a theoretical and an empirical perspective, such as McAndrews and Wang (2012), Wang and Wolman (2016), and Alvarez and Lippi (2017).[2] An important point highlighted in these studies is that consumers and businesses face positive externalities in adopting and using cashless payments. Our results suggest that Japan's program promoting cashless payments raised the number of credit card users, which in turn increased the benefits of using credit cards (i.e., externalities), so that consumers did not switch back to cash payments even after the program had ended.

The second strand of literature to which this study is related focuses on the diffusion of new technologies and products. Griliches (1957) and Jovanovic and Wang (2020), for example, use the logistic function as a tool to describe the speed and upper limit of diffusion, while Young (2009) and Mobius and Rosenblat (2014) construct models of diffusion in terms of social learning or contagion. Their models describe developments in the share of adopters of a new technology over time, depending on different assumptions on how information about new technologies is transmitted. Our results indicate that policy intervention by the government accelerated the speed of technology adoption regarding cashless payments, and that the impact of this intervention decreased as the use of cashless payments increased.

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[2]Other studies on this topic include Borzekowski et al. (2008), Klee (2008), Bourguignon et al. (2014), Koulayev et al. (2016), Jonker et al. (2017), and Wakamori and Welte (2017).

The third strand of literature focuses on effects of the COVID-19 pandemic on consumers' choice of payment method. For example, Cevik (2020), Chen et al. (2020), and Wisniewski et al. (2021) document that consumers decreased the use of cash to avoid the risk of infection, while Rogoff and Scazzero (2021) show that the use of electronic payments increased during the pandemic period. In this study, we empirically show that the COVID-19 pandemic promoted the use of credit cards and its impact was heterogeneous across restaurants. More specifically, we show that restaurants that did not participate in the point reward program experienced higher growth in credit card spending than participating restaurants (after controlling for the negative impact due to people avoid outings during the pandemic).

The remainder of the study proceeds as follows. The next section provides a brief overview of Japan's point reward program for cashless payments. Section 3 explains the data used for the analysis. Section 4 describes the methodology we employ to examine the impact of the program. Section 5 presents empirical results, while Section 6 provides various robustness checks. Finally, Section 7 concludes.

2 Overview of Japan's Point Reward Program

The Japanese government implemented the point reward program for cashless payments from October 2019 to June 2020 with the aim of boosting consumption expenditure after the standard consumption tax rate increased from 8 to 10 percent. This program to stimulate demand was unique in that the point rewards consumers could receive depended solely on their method of payment: consumers could receive points if they used a cashless payment method (such as paying by credit or debit card, by QR code using their mobile phone, or using e-money) when purchasing a product from a participating business but could not receive points if they chose to pay by cash for the same purchase. The program therefore incentivized consumers to switch from cash to cashless payments.

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Consumers in most cases received point rewards equivalent to 5 percent of the value of the purchases.[3] Moreover, this program included several policy measures to encourage merchants to adopt cashless payment methods. Specifically, the government covered retailers' costs of adopting payment terminals and shouldered part of the transaction fees, in order to incentivize businesses as well as consumers to go cashless.

However, businesses needed to meet certain conditions to participate in the point reward program. Cafes and restaurants, for example, had to satisfy at least one of the following two conditions: (i) the paid-in capital of the firm operating the business could not exceed 50 million yen, and/or (ii) they could not have more than 100 employees. The purpose of these conditions was to boost demand primarily for such smaller businesses. These conditions enable us to treat the program as a quasi-experiment and compare the use of cashless payments at participating and non-participating businesses.

Japan's government program differs from the incentive schemes examined in other studies in several respects. Ching and Hayashi (2010) and Carbó-Valverde and Liñares-Zegarra (2011), for example, examine the impact of point reward programs implemented by card issuers, not the government. The purpose of the point reward programs by card issuers was to promote a brand. In contrast, Japan's program offered the same rewards for all card issuers and providers of other cashless payment services to promote cashless payments throughout the economy. Meanwhile, the study by Jonker et al. (2017) focuses on a nationwide campaign in the Netherlands to promote debit card usage that, however, did not provide financial incentives. While this campaign may have led consumers and businesses to switch to cashless payments based on the expectation that everyone else would be switching, it likely was less effective than Japan's program that provided financial incentives.

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[3]The rate of points was 2 percent (offsetting the consumption tax hike) for purchases at retail shops belonging to large franchise chains.

3 Data

We use two sets of data for our analysis. The first is a list of restaurants participating in the point reward program, which was compiled by the Ministry of Economy, Trade, and Industry of Japan (METI). This list includes the name of each restaurant, the cashless payment methods available, and the date that a restaurant joined the program. Because it took time for the government to verify that restaurants satisfied the conditions mentioned in the preceding section, in many cases applications were approved only after the program had started in October 2019.

The second dataset we use consists of credit card transaction records for restaurants located in Shinjuku, a major business and shopping district in central Tokyo, provided by JCB, a major card brand in Japan. The total number of restaurants covered in this dataset is 8,241. Checking the names of these restaurants against METI's list, we find that 2,129 of these 8,241 restaurants participated in the program. The observation period for this dataset is from April 2018 to December 2020, and the dataset allows us to observe on a monthly basis how much individual card users paid at particular restaurants. It should be noted, however, that the identifiers of individual card users are reshuffled quarterly to protect their privacy.

Based on this dataset, Figure 1 shows monthly developments in the amount of JCB credit card spending, the number of card users at restaurants in Shinjuku, Tokyo, and the number of restaurants accepting payment by credit card. The figure indicates that while credit card spending displays strong seasonality, spending accelerated rapidly following the start of the point reward program in October 2019. A similar pattern is observed for the number of card users. However, these values declined substantially in December 2019 and reached a low in April 2020, when the first surge of COVID-19 hit Japan.[4] The figure also indicates that the number of restaurants that accept credit card payment increased steadily, while the number

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[4]While our dataset is restricted to one particular area in Japan, developments in the data closely follow those in nationwide restaurant sales.
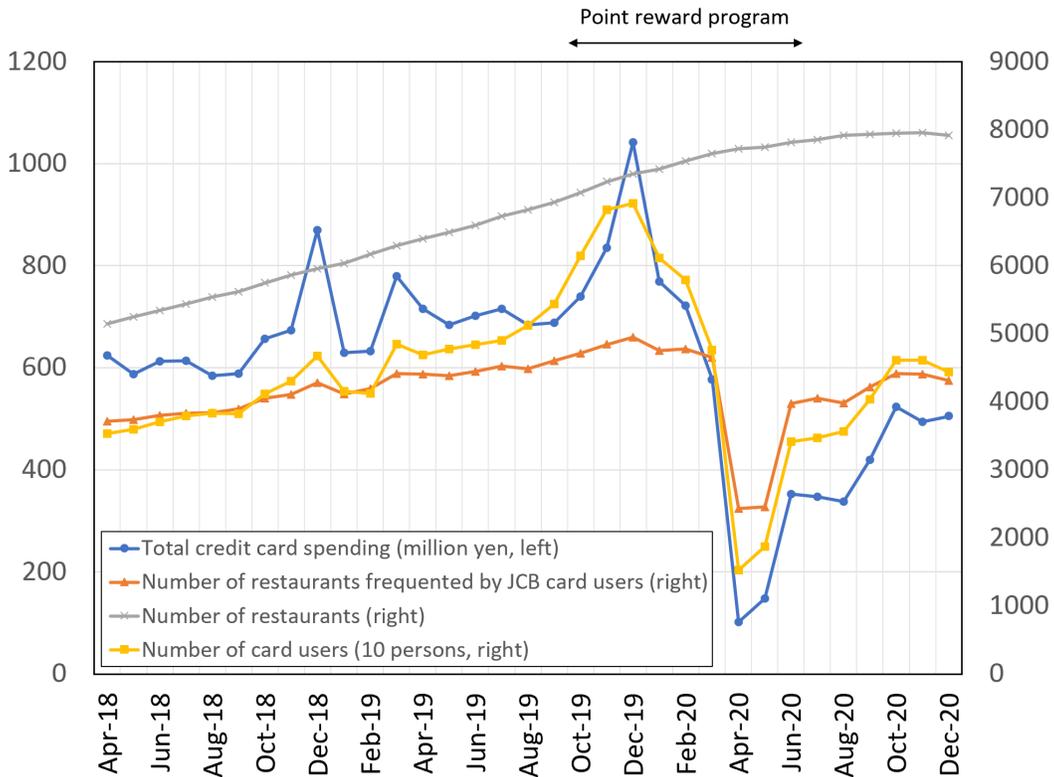
Figure 1: Monthly developments in credit card usage from April 2018 to December 2020

Notes: The figure shows the total amount of JCB credit card spending at restaurants in Shinjuku, Tokyo, the number of card users at these restaurants, the number of restaurants accepting payment by credit card, and the number of restaurants for which there are records of credit card transactions in our JCB card database (i.e., restaurants frequented by JCB card users).

of restaurants for which our database shows actual transactions was more volatile.

As a preliminary check, Figure 2 compares the growth rates of spending at restaurants that participated in the point reward program (the treatment group) and those that did not (the control group). Specifically, we calculate the year-on-year rate of change in spending at each restaurant for each month and take the median for each group. The figure indicates that the growth rates for both groups were very similar prior to the program, but the treatment group experienced higher growth in January and February 2020, suggesting that the program had a positive impact. It should be noted that we can calculate year-on-year growth rates only for restaurants that had been accepting credit cards for at least a year, meaning that
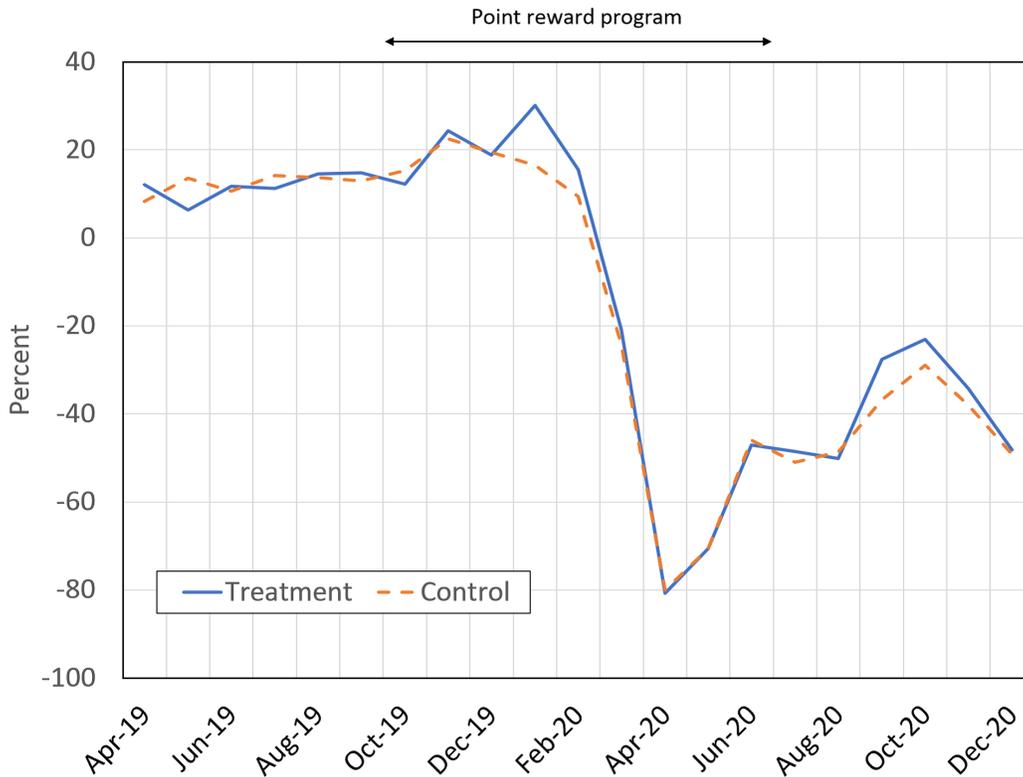
Figure 2: Comparison of spending growth rates

Notes: The figure shows the growth rate of JCB credit card spending for the treatment and control groups from April 2019 to December 2020. See the text for a full description.

restaurants that had only just started accepting credit cards are excluded in Figure 2.

4   Methodology

Using records of credit card transactions at restaurants in Tokyo from April 2018 to December 2020, we examine the impact of the point reward program for cashless payments.

As mentioned earlier, the impact of the program can be decomposed into two parts: the extensive margin (the increase in consumers using cashless payment methods) and the intensive margin (the increase in the frequency and/or amount of cashless payments). The purpose of Japan's program was to increase both. In practical terms, the implications are

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as follows. Given that in 2018 there were already 280 million credit cards—or 2.3 cards per capita—in circulation in Japan,[5] most consumers already had a credit card before the program started. This means that the extensive margin can be regarded as the increase in the number of consumers using new cashless payment methods, such as payment by QR code, while the intensive margin can be regarded as the increase in the frequency and amount of payments by existing cashless payment methods (i.e., credit cards).

Our focus is on the impact of the point reward program on credit card usage, i.e., the intensive margin. More specifically, an increase in the intensive margin means that consumers who already have credit cards use them at more payment opportunities. For example, consumers that used to pay at restaurants in cash choose to pay by credit card instead. In this case, the adoption process of credit card payments can be described as follows. Suppose that the set of customers of a particular restaurant is fixed. In the beginning, all customers choose to pay by cash; however, they gradually switch to paying by credit card over time.[6]

In this study, we regard the spread of cashless payment methods (e.g., credit cards) as technology adoption, which can be modelled by the following simple equation:

$$\Delta x_{it} = \lambda(1 - x_{i,t-1}), \tag{1}$$

where x_{it} represents the fraction of cashless payments at restaurant i in period t, and λ denotes the probability with which customers using cash in the previous period switch to cashless payment in the current period. Equation (1) shows that the increase in cashless

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[5]These numbers are reported in the BIS statistics on payments, which can be accessed via the following website: https://www.bis.org/statistics/payment_stats.htm.

[6]Previous studies have proposed two types of diffusion models that potentially describe the adoption of payment by credit card. The first type focuses on the aspect of externalities in using a particular payment method, as considered by McAndrews and Wang (2012). The other type highlights the aspect that adopters of a new technology have some influence on non-adopters' behavior through networks, as described by Young (2009). More specifically, contact with adopters may directly change non-adopters' choice (contagion), or indirectly provide information persuading non-adopters to adopt the new technology (social learning). These studies can be arguably regarded as focusing on the extensive margin, while our study mainly examines the intensive margin.
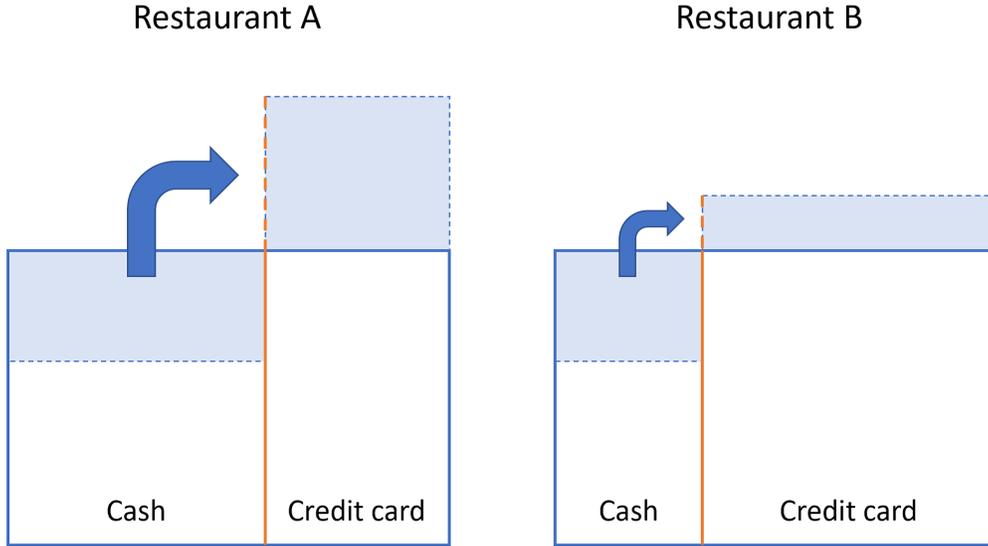
Figure 3: Illustration of the switch from cash to credit card payments

payments (Δx_{it}) depends on two factors. The first is the speed at which customers switch from cash to cashless payments (λ), which is an exogenous parameter and increased due to the point reward program. The second is the fraction of cash users $(1 - x_{i,t-1})$, which takes a larger value at an earlier stage of the adoption process.[7]

Figure 3 provides an illustration of the adoption process. The set of customers at Restaurant A is represented by the blue line. A certain fraction of customers choose to pay in cash, while the remaining customers pay by credit card (or other cashless payment methods). The point reward program provided cash users with an incentive to switch to paying by credit card, and some of them do switch, as denoted by the shaded area. Because the fraction of cash users at Restaurant A is high, the impact of the point reward program to promote cashless payment is large. In contrast, the fraction of cash users at Restaurant B is small (in other words, the adoption of cashless payment in this restaurant is more advanced). Given

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[7]In statistics, this is called the Poisson process, where an event (such as the switch to cashless payments in our case) occurs at a constant probability. If we assume $x_{i0} = 0$ for the initial period, the solution to this equation is given by $x_{it} = 1 - \exp(-\lambda t)$.

that the probability with which cash users switch to credit cards is assumed to be identical across restaurants, the impact of the point reward program is smaller than at Restaurant A. What matters for our analysis here is that the fraction of cash users differs between these two restaurants, which is denoted by the orange line. Although our dataset does not include cash transactions, we can proxy the location of the orange line by the time that has elapsed since a restaurant started accepting credit card payments. Using this approach, we empirically test the model.

To discuss how our model is related to those used in earlier studies, we employ the following extended version of Equation (1):

$$\Delta x_{it} = (\theta x_{i,t-1} + \lambda)(1 - x_{i,t-1}). \tag{2}$$

In this equation, the fraction of cash users still plays a role in determining the increase in cashless payments; however, the probability with which they switch to cashless payments is more complex. Specifically, λ is an exogenous parameter capturing the impact of the point reward program, while $\theta x_{i,t-1}$ is an endogenous variable that captures the effect of imitation; i.e., the more customers use cashless payments, the higher is the probability with which cash users switch to cashless payments (where $\theta > 0$). This can be interpreted as the impact of the diffusion of cashless payment technology. If we assume $\lambda = 0$, Equation (2) reduces to the standard logistic function.[8]

To quantify the heterogeneous impact of the point reward program depending on the stage of the adoption process, we estimate the following:

$$\ln\left(y_{it} + \sqrt{y_{it}^2 + 1}\right) = \alpha(s_{it})D_{it} + \beta(s_{it})H_{it} + \gamma_i + \delta_t + \epsilon_{it}, \tag{3}$$

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[8]In the general case where $\lambda > 0$, and assuming $x_{i0} = 0$ for the initial period, the solution of Equation (2) is $x_{it} = \frac{1-\exp(-(\theta+\lambda)t)}{1+(\theta/\lambda)\exp(-(\theta+\lambda)t)}$. The relationship between these equations is discussed by Young (2009).

where y_{it} denotes the amount paid via credit cards at restaurant i in month t.[9] D_{it} is a dummy variable that takes one if restaurant i participated in the program in month t, and zero otherwise. H_{it} is another dummy variable that takes one if restaurant i participated in the program and t is one of the months from July to December 2020.[10] Note that the coefficients on these dummy variables (α and β) depend on how long a restaurant has been accepting payment by credit card (measured in terms of s_{it}, the number of quarters that have elapsed since restaurant i started accepting credit card payments), which we use as a proxy for the extent to which customers of a particular restaurant adopted payment by credit card. Finally, γ_i denotes restaurant fixed effects, while δ_t represents time fixed effects.[11] ϵ_{it} is the error term.

The parameters of interest in Equation (3) are $\alpha(\bar{s})$, $\beta(\bar{s})$, and $\frac{\partial \alpha}{\partial s_{it}}$. First, $\alpha(\bar{s})$ represents the average impact of the point reward program on credit card spending at restaurants that participated in the program from October 2019 to June 2020 (i.e., the treatment effect), where $\bar{s}$ denotes the average of the adoption of credit card payments across restaurants. We estimate this parameter based on a staggered difference-in-differences approach. Second, $\beta(\bar{s})$ represents the average impact of the point reward program on credit card spending at participating restaurants *after* the program. As discussed, this program accelerated the adoption of credit card usage, indicating that its impact persisted after the program ended, even though the financial incentive provided by the government was temporary. The parameters α and β are expected to be positive. Third, $\frac{\partial \alpha}{\partial s_{it}}$ denotes the dependence of the treatment effects on the degree to which cashless payments had been adopted at individual restaurants. This

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[9]The payment amounts at different restaurants and in different months follow highly skewed distributions and there are many cases in which the payment amount is zero. We therefore use a transformation called the inverse hyperbolic sine rather than the natural logarithm. See Burbidge et al. (1988) for a detailed discussion.

[10]This dummy variable captures the potential effect of the point reward program after it ended in June 2020.

[11]We also use time fixed effects specific to types of restaurants and find that the results are almost identical to those presented below. Specifically, we classify restaurants covered in the dataset into cafes, Japanese-style restaurants, non-Japanese-style restaurants, chain restaurants, bars, and Japanese-style pubs.

parameter is expected to be negative, which we estimate by including the interaction term $s_{it} \times D_{it}$ as an explanatory variable.

5 Estimation Results

5.1 Baseline Results

The estimation results are shown in Table 1. First, column (1) indicates that the point reward program had a significant positive impact on credit card spending, which is estimated to have increased by 46 percent on average. In column (2), the sample is restricted to restaurants that had at least one record of a credit card transaction during the first surge of COVID-19 (April and May 2020). In this case, the impact of the program is estimated to be 26 percent, which is somewhat smaller but still statistically significant. Second, columns (3) and (4) show that the impact on credit card spending at restaurants in the treatment group was positive and significant after the point reward program ended, suggesting that the impact of the program persisted and was not simply transitory. Third, columns (5) and (6) indicate that the more advanced the adoption of credit card payments at a restaurant, the smaller was the impact of the program.

In Table 2, we use the number of credit card users instead of spending as the dependent variable. The results are very similar. Specifically, the impact of the program on the number of credit card users at restaurants in the treatment group was positive and significant both during and after the program. In addition, the impact was smaller at restaurants that were more advanced in the adoption of credit cards (i.e., where already a larger number of customers were making payments by credit card).

Next, we estimate the impact of the point reward program on a monthly basis by defining the dummy variables for the treatment group for each of the months from October 2019 to December 2020. In this estimation, we also include a dummy variable that takes a value

Table 1: Impact of the point reward program on credit card spending

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	0.461	0.262	0.596	0.387	1.134	1.177
	(0.071)	(0.076)	(0.090)	(0.094)	(0.121)	(0.131)
H_{it}			0.448	0.418	1.130	1.319
			(0.121)	(0.139)	(0.165)	(0.192)
$s_{it} \times D_{it}$					-0.025	-0.033
					(0.003)	(0.003)
$s_{it} \times H_{it}$					-0.029	-0.035
					(0.004)	(0.005)
R^2	0.566	0.450	0.566	0.451	0.565	0.452
Restaurants	8,241	3,195	8,241	3,195	8,204	3,171
Observations	207,936	91,911	207,936	91,911	206,796	91,119

Notes: In columns (1), (3), and (5), the sample includes all restaurants but excludes observations for the period of the first surge of COVID-19 (April and May 2020). In columns (2), (4), and (6), the sample is restricted to restaurants for which there was at least one observation for this period. Standard errors clustered at the restaurant level are reported in parentheses.

Table 2: Impact of the point reward program on the number of card users

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	0.124	0.094	0.143	0.137	0.281	0.396
	(0.016)	(0.020)	(0.021)	(0.026)	(0.029)	(0.036)
H_{it}			0.061	0.141	0.273	0.435
			(0.029)	(0.037)	(0.041)	(0.052)
$s_{it} \times D_{it}$					-0.0063	-0.0110
					(0.0008)	(0.0009)
$s_{it} \times H_{it}$					-0.0091	-0.0112
					(0.0012)	(0.0015)
R^2	0.775	0.748	0.775	0.749	0.775	0.750
Restaurants	8,241	3,195	8,241	3,195	8,204	3,171
Observations	207,936	91,911	207,936	91,911	206,796	91,119

Notes: In this table, the number of card users (instead of spending) is used as the dependent variable. All other settings are the same as in Table 1.
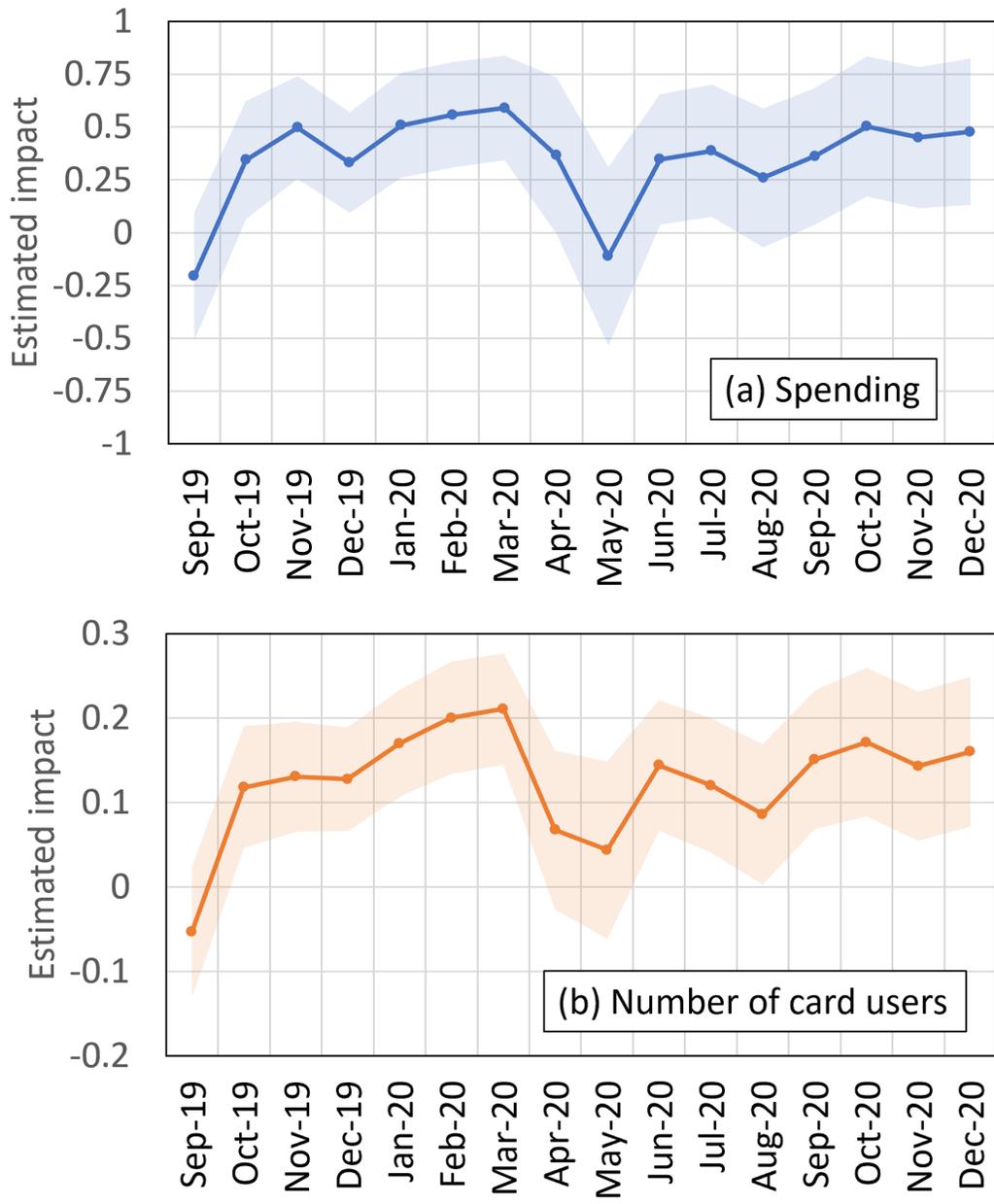
Figure 4: Monthly impact of the point reward program on credit card use

Notes: This figure shows the estimated coefficient on the dummy variable for participating restaurants in each month. The shaded areas denote the 95 percent confidence intervals. The sample and specification used in these panels are essentially the same as those used in column (4) of Tables 1 and 2.

of one for the month of September 2019—the month before the program took effect—for restaurants that participated in the program in October 2019. The purpose of this "placebo variable" is to examine whether there are any systematic differences in terms of credit card spending and/or the number of card users between the treatment group and the control group.

Panel (a) of Figure 4 shows that the monthly impact of the program was significantly positive for most of the period from October 2019 to December 2020 (the exception being the period of the first surge in COVID-19 infections in April and May 2020 and the second surge in August 2020), and that there was no significant placebo effect in September 2019. This finding is consistent with our hypothesis that restaurants that participated in the program saw a faster increase in payments by credit card. Panel (b) shows the monthly impact on the number of credit card users. The pattern is very similar to Panel (a). We discuss why the impact of the point reward program was smaller during the first surge of COVID-19 in the next part.

5.2 Impact of the COVID-19 Pandemic on the Choice of Payment Method

In our observation period, not only the point reward program but also the COVID-19 pandemic may have influenced the payment method used by consumers (as discussed by Cevik 2020 and Wisniewski et al., 2021). In this part, we examine the impact of the COVID-19 pandemic.

We again use the framework shown in Figure 3. Specifically, the pandemic has had two different effects on payment behavior. First, people have refrained from going out during the pandemic, leading to a decrease in the number of customers and hence credit card users at restaurants. We assume that the extent to which restaurants are affected by this is identical across restaurants participating and not participating in the point reward program, so that

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this effect is absorbed by the time fixed effects. Second, during the pandemic, some customers previously using cash switched to credit cards in an attempt to reduce the risk of infection. We assume that customers that visited restaurants in this period were identical in terms of their behavior to avoid infection, meaning that the probability with which cash users switched to cashless payments was identical across restaurants. This implies that the share of cash users plays a central role in determining the impact of the pandemic to promote cashless payments, as discussed in Section 4. On the one hand, the share of cash users at restaurants that participated in the point reward program was already small just before the surge of COVID-19 infections in April and May 2020, since many cash users had already switched to paying by credit card due to the program (as at Restaurant B). On the other hand, the share of cash users at restaurants that did not participate in the program (as at Restaurant A) was still large since the customers of those restaurants could not take advantage of the program, suggesting that the impact of the COVID-19 pandemic on card usage was heterogeneous across participating and non-participating restaurants.

We examine the impact of the pandemic in two ways. First, we use the fact that the Japanese government declared a state of emergency in Tokyo from April 7, 2020, to May 25, 2020. The state of emergency highlighted the risk of infection and may have led people to pay by card even at restaurants that did not participate in the point reward program. It is therefore likely that the difference between restaurants participating and not participating in the program in terms of customers' use of credit cards became smaller. To test this, we construct a dummy variable, C_t, that takes one during the state of emergency period and zero otherwise, and add the interaction term $D_{it} \times C_t$ as an explanatory variable in the baseline estimation. Second, we use the mobility data provided by Google. Given that avoiding outings and switching to cashless payments have the same purpose of reducing the risk of infection, it is likely that the extent to which consumers engaged in these behaviors is closely linked. This implies that people were more likely to switch to cashless payment methods at
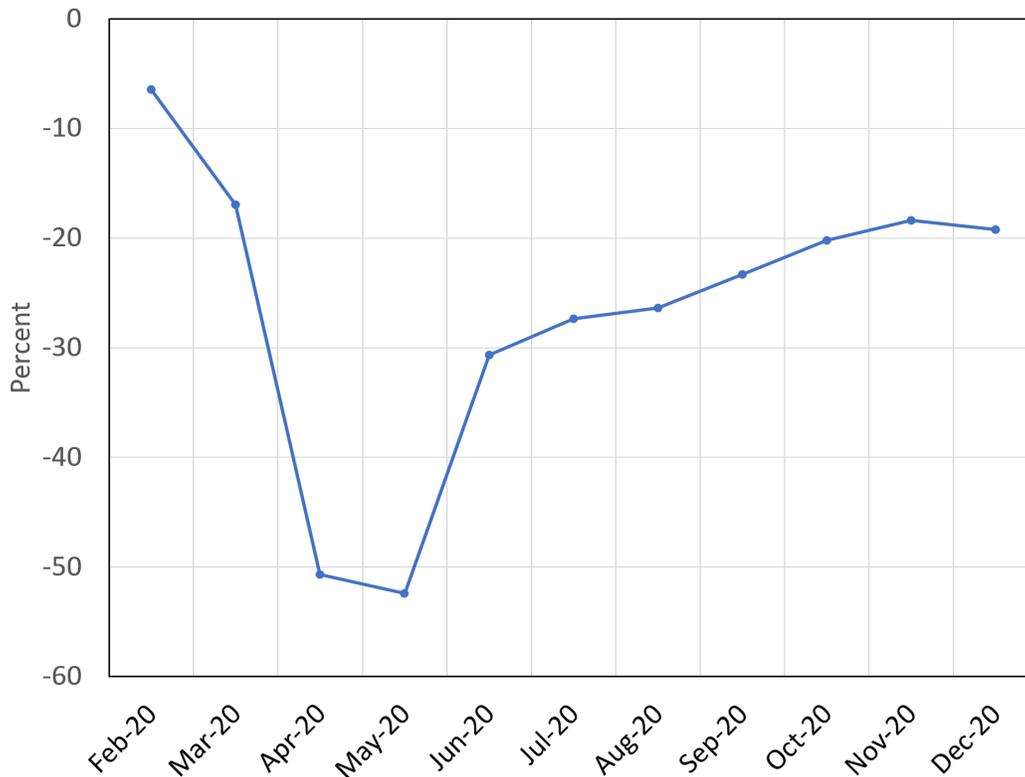
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Figure 5: Number of people visiting retail shops during the pandemic

Notes: This figure shows the year-on-year rate of change in the number of people visiting retail shops in Tokyo from February to December 2020. The original data provided by Google are daily data, which we convert to monthly data by taking the simple average.

times that they also refrained more from going out. We therefore use the Google mobility data as a proxy for payment behavior. Specifically, we include the interaction term $D_{it} \times m_t$ in the estimation, where m_t denotes the year-on-year rate of change in the number of visitors to retail shops in Tokyo (which is shown in Figure 5).[12]

The results are presented in Tables 3 and 4. Table 3 shows that restaurants that participated in the point reward program from October 2019 to June 2020 experienced higher growth in both credit card spending and the number of card users, but that most of the impact of the program vanished during the state of emergency period (the coefficients on

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[12]The Google dataset reports the numbers from February 2020, which we use in this estimation. For other periods, we impute $m_t = 0$ assuming that the impact of the point reward program was unrelated to the number of people going out before the COVID-19 pandemic.

Table 3: Impact of the point reward program during the state of emergency period

	Payment amounts		Number of card users	
Explanatory variables	(1)	(2)	(3)	(4)
D_{it}	0.346	0.466	0.121	0.162
	(0.076)	(0.091)	(0.019)	(0.024)
$D_{it} \times C_t$	-0.346	-0.332	-0.109	-0.104
	(0.127)	(0.128)	(0.037)	(0.038)
H_{it}		0.414		0.140
		(0.139)		(0.037)
R^2	0.450	0.451	0.748	0.749
Restaurants	3,195	3,195	3,195	3,195
Observations	91,911	91,911	91,911	91,911

Notes: C_t is a dummy variable that takes one for April and May 2020 (the state of emergency period), and zero otherwise. Standard errors clustered at the restaurant level are reported in parentheses.

Table 4: Impact of the point reward program and the number of people going out

	Payment amounts		Number of card users	
Explanatory variables	(1)	(2)	(3)	(4)
D_{it}	0.389	0.505	0.130	0.169
	(0.084)	(0.094)	(0.022)	(0.025)
$D_{it} \times m_t$	0.0067	0.0063	0.0018	0.0017
	(0.0027)	(0.0027)	(0.0008)	(0.0008)
H_{it}		0.829		0.279
		(0.405)		(0.099)
$H_{it} \times m_t$		0.0185		0.0062
		(0.0159)		(0.0038)
R^2	0.450	0.451	0.748	0.749
Restaurants	3,195	3,195	3,195	3,195
Observations	91,911	91,911	91,911	91,911

Notes: m_t denotes the year-on-year rate of change in the number of people visiting retail shops in Tokyo. Standard errors clustered at the restaurant level are reported in parentheses.

$D_{it} \times C_t$ are negative and statistically significant). This is consistent with the finding in Figure 4 that the impact of the program is not statistically significant for this period, suggesting that cash users switched to credit cards even at non-participating restaurants in order to avoid the risk of infection.

By comparing the results in Tables 2 and 3, we can estimate the impact of the COVID-19 pandemic on the choice of payment method relative to the point reward program. First, looking at column (4) of Table 2 as an example, the coefficient on the dummy variable for participating restaurants is 0.137, while the corresponding value in column (4) of Table 3 at 0.162 is considerably larger. This indicates that by controlling for the emergency period, we can remove biases from the estimated impact of the point reward program. Second, the coefficient estimates for the dummy variable for the period after the program in these tables are 0.141 and 0.140, indicating that they are not subject to biases. Third, the coefficient estimate for the interaction term in column (4) of Table 3 is -0.104 and statistically significant. This finding indicates that while the pandemic had an impact on both restaurants that participated and restaurants that did not participate in the point reward program, the impact of the pandemic was larger for non-participating restaurants (due to the larger share of cash users). Quantitatively, while the impact of the program was 0.162, that of the pandemic was $0.104 + g$ for non-participating restaurants and g for participating ones, where g is the impact of the COVID-19 surge on credit card usage common across restaurants ($g > 0$). If g is very close to zero, the impact of the pandemic was 0.104 for non-participants, which is the most conservative estimate (around two-thirds of the impact of the point reward program). On the other hand, if g is somewhat positive, the pandemic may have had a larger impact on consumers' choice of payment method than the point reward program.

Next, Table 4 reports how the impact of the program depends on the number of people going out. In column (1), for example, the average impact of the program is estimated to be 0.389 and the coefficient on the interaction term is estimated to be 0.0067 (both are

statistically significant). The number of people going out decreased by 50 percent in April 2020, meaning that the impact of the program declined by 0.335 (= 0.0067×50) in this month. The other columns show similar results. In sum, during the first surge of COVID-19, the difference between restaurants participating and not participating in the program in terms of customers' use of credit cards decreased.

6 Robustness Checks

6.1 Robustness Check Using Similar Restaurants

Of the roughly 8,000 restaurants in our sample, around 2,000 participated in the point reward program, while the remaining 6,000 did not. This large asymmetry in the number of restaurants that participated and those that did not suggests that the two groups may differ in terms of their underlying characteristics. In this part, we address this issue.

We check the robustness of the baseline results focusing on restaurants that are similar. Specifically, we take advantage of the fact that the database we use provides anonymized identifiers of individual credit card users.[13] Using the identifiers of credit card users at participating restaurants, we calculate the share that the card spending of these customers accounts for in the total card spending at each non-participating restaurant. If this share is high, a non-participating restaurant is similar to participating restaurants in that they are frequented by similar customers. Based on this criterion, we construct a sample in which the number of non-participating restaurants is equal to that of participating restaurants and repeat the baseline estimation.

The estimation results are presented in Tables 5 and 6. Columns (1) and (2) of Table 5 indicate that the point reward program increased the amount paid by credit card by 25-52

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[13]As mentioned, such identifiers, in addition to being anonymized, are reshuffled quarterly for privacy protection.

Table 5: Robustness check using similar restaurants: Spending

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	0.522	0.257	0.499	0.273	1.020	1.076
	(0.086)	(0.085)	(0.105)	(0.103)	(0.130)	(0.136)
H_{it}			-0.082	0.059	0.651	1.002
			(0.142)	(0.153)	(0.181)	(0.204)
$s_{it} \times D_{it}$					-0.025	-0.034
					(0.003)	(0.003)
$s_{it} \times H_{it}$					-0.032	-0.036
					(0.005)	(0.005)
R^2	0.559	0.436	0.559	0.436	0.558	0.439
Restaurants	4,258	2,156	4,258	2,156	4,236	2,141
Observations	105,468	61,269	105,468	61,269	104,793	60,774

Notes: The table shows the estimation results based on a sample consisting of similar restaurants. See the text for how this sample is constructed. Standard errors clustered at the restaurant level are reported in parentheses.

Table 6: Robustness check using similar restaurants: Number of card users

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	0.138	0.069	0.110	0.073	0.247	0.336
	(0.019)	(0.022)	(0.023)	(0.029)	(0.030)	(0.038)
H_{it}			-0.106	0.013	0.125	0.320
			(0.032)	(0.040)	(0.042)	(0.055)
$s_{it} \times D_{it}$					-0.0067	-0.0113
					(0.0008)	(0.0009)
$s_{it} \times H_{it}$					-0.0102	-0.0118
					(0.0012)	(0.0015)
R^2	0.758	0.721	0.758	0.721	0.758	0.725
Restaurants	4,258	2,156	4,258	2,156	4,236	2,141
Observations	105,468	61,269	105,468	61,269	104,793	60,774

Notes: In this table, the number of card users (instead of spending) is used as the dependent variable. All other settings are the same as in Table 5.

percent, which is similar to the baseline results. However, columns (3) and (4) show that this positive impact did not persist after the program ended in June 2020. One possible interpretation is that the COVID-19 pandemic led people to use cashless payment methods at non-participating restaurants (as shown in the previous section), so that the difference between participants and non-participants of the program is not statistically significant. Columns (5) and (6) indicate that the coefficients on the interaction terms are negative and statistically significant, which is consistent with the baseline results. Similar findings are obtained in Table 6, where the number of card users is used as the dependent variable.

6.2 Robustness Check: Potential Bias due to Heterogeneous Treatment Effects

The baseline analysis showed that the impact of the points reward program was heterogeneous in that the size of the impact depended on how advanced the adoption of credit card payments at a particular restaurant already was when the program started. However, the presence of such heterogeneity means that the estimates of the average treatment effect may be incorrect, as discussed, for example, by de Chaisemartin and D'Haultfœuille (2020) and Goodman-Bacon (2021). In this subsection, we address this issue.

De Chaisemartin and D'Haultfœuille (2020) provide a clear description of the circumstances under which estimates may be incorrect. They show theoretically that the average treatment effect is obtained as the weighted sum of individual treatment effects, i.e., difference-in-differences that compare the outcomes between consecutive time periods across groups. This means that a group classified as the control group in a comparison may be treated in both periods, so that the individual treatment effect regarding this group will be subtracted in the next period, to which negative weights are assigned. Thus, given that these effects are heterogeneous across groups or periods, the average treatment effect may be biased.

Table 7: Robustness check: Potential bias arising from heterogeneous treatment effects

	Payment amounts		Number of card users	
Explanatory variable	(1)	(2)	(3)	(4)
D_{it}	0.350	0.485	0.095	0.180
	(0.077)	(0.099)	(0.014)	(0.023)
Observations	207,936	91,911	207,936	91,911

Notes: The table reports the estimation results based on de Chaisemartin and D'Haultfœuille's (2020) method, which addresses heterogeneity in treatment effects. The estimation includes fixed effects for restaurants and periods. Standard errors clustered at the restaurant level are reported in parentheses.

We address this issue by following the estimation method proposed by de Chaisemartin and D'Haultfœuille, which consists of two parts. The first is to simply calculate the fraction of negative weights, which we find to be very small (less than 5 percent) in our dataset. This suggests that the baseline estimates are unlikely to be sensitive to heterogeneity. The second part is to obtain estimates of the average treatment effect that are robust to heterogeneous treatment effects by using their computation package (called *fuzzydid* in Stata). The results are shown in Table 7 and are essentially similar to those in Tables 1 and 2; however, in this table the impact of the program is larger for small sample cases (columns (2) and (4)) than large sample cases (columns (1) and (3)), which is somewhat different from the baseline results.

7   Concluding Remarks

In this study, we examined the impact of Japan's point reward program for cashless payments using credit card transaction data. Our main findings are as follows. First, the program had a positive impact on both the amounts paid by credit card and the number of card users. Second, this positive impact persisted even after the program ended in June 2020. Third, the impact of this program depended on the extent to which customers of a restaurant had

already adopted payment by credit card.

Our findings have two policy implications. First, we showed that the impact of the point reward program is persistent rather than transitory, so that the government program to promote cashless payments was effective during and after the surges in COVID-19 infections. Our results indicate that the impact of the government program in terms of boosting cashless payments was comparable to that of the risk of infection, although we estimated the lower bound of the impact of COVID-19, not the impact itself. Second, we showed that the program had heterogeneous impacts depending on the stage of the adoption process. This is informative for policy makers in promoting the adoption of new technologies such as FinTech or a central bank digital currency.

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